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Jobs!

Electricity Shortages and Unemployment in Africa

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Abstract

To what extent does unreliable electricity provision pervasive in many African countries affect job creation in the region? This paper addresses the question by assembling household and firm level data from 29 African countries along with unique project level data on foreign direct investment (FDI). Leveraging several quasi-experimental approaches, the paper shows that outages have a non-trivial negative impact on employment. The effect is driven by a reduction in employment in non-agricultural sectors and skilled jobs. Unskilled jobs are unaffected by electricity outages. The negative effect of outages on firm entry and the performance of incumbent firms are plausible channels..

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1 Introduction

Electricity is considered one of the basic attributes of modern life. It is a key input for the production of goods and services, as well as quality of life. The reality, however, is that despite the fact that more than 580 million people in Africa lack access to electricity (IEA, 2019), the quality of supply to connected households and firms is precarious. Electricity outages have become a common feature in many African countries (Andersen and Dalgaard, 2013; Blimpo and Cosgrove-Davies, 2019).

A large body of development literature has underscored the importance of electricity access on socioeconomic outcomes such as education, income, health and labor allocation (Dinkelman, 2011; Lipscomb et al., 2013; Abbasi et al., 2022). Yet little is known about the economic impact of unreliable electricity services. Available studies on the impact of electricity outages have largely focused on the extent to which outages affect firm productivity (Allcott et al., 2016; Abeberese et al., 2021) and profitability (Cole et al., 2018; Hardy and McCasland, 2019). An important yet often ignored question is the extent to which persistent electricity shortages affect job creation and consequently, the rate of unemployment in the developing world.

The main goal of this paper is to show evidence of how electricity shortages[1] constrain job creation in the developing world. Specifically, using instrumental variable regression, difference-in-difference, and fixed effect estimators with recent data on households (individuals) and firms in 29 African countries, I estimate the causal impact of electricity shortages on employment in Africa, and document the mechanisms through which the supply inefficiencies affect job creation. The paper hypothesizes and tests two main channels through which persistent electricity outages affect job creation and hence unemployment: (i) on the extensive margin, persistent outages create distortions in the business climate and increase the expected cost of doing business. This can discourage potential en-

[1] In the remainder of this paper, electricity outages and shortages are used interchangeably.

trepreneurs (investors) from establishing (investing in) businesses that would otherwise have employed people. As a result, persistent outages could reduce entry of domestic and foreign (via foreign direct investment (FDI)) firms;[2] (ii) In the intensive margin, shortages in electricity supply exert adverse impact on firms' productivity and profit, given that electricity is an important factor of production. Therefore the negative impact of outages on firm performance can have negative consequences on firms' demand for labor.

Causal estimation of the impact of infrastructure services such as the quality of electricity is often beset with the challenge of endogeneity, as the incidence and intensity of electricity outages are non-random across space and time.[3] Local economic, social and political factors may confound the relationship between outages and the outcome variables of interest. To overcome this challenge of identification, the paper uses several estimation strategies namely: instrumental variable (IV), difference-in-difference (DID), synthetic control, and panel fixed effects.

The empirical strategy of the paper is summarized as follows: In the main analysis, I use an IV strategy that exploits plausibly exogenous variations in the incidence of outages induced by variations in lightning strikes across space and time. Lightning strikes are known to be a major cause of surges in electrical systems leading to over-voltage and destruction of power infrastructure thereby causing outages (Andersen et al., 2011, 2012; Andersen and Dalgaard, 2013). Leveraging this relationship between lightning activities and electricity outages, I combine granular data on measures of lightning intensity with two rounds of individual surveys from the Afrobarometer dataset in 25 countries to estimate an IV regression of the effect of outages on employment. The identifying assumption advanced here is that lightning strikes influence labor market outcomes only through the effect on the quality of electricity supply, i.e, the so-called "exclusion restriction assump-

[2]The high cost of business associated with outages could also facilitate the exit of firms either through relocation to other countries (cities) with much reliable electricity supply, or firm shut down.

[3]Like most essential services, random assignment of outages across locations is not feasible from a policy perspective and more importantly, unethical.

tion". The main threat to this assumption relates to the possibility of lightning strikes influencing labor market via channels such as information technology (IT) adoption by firms (households) and the consequent effect on demand (supply) for labor as lightning has been shown to affect the diffusion of technologies such as mobile phones and computers (Andersen et al., 2012; Manacorda and Tesei, 2020; Guriev et al., 2020). To address this concern, I control for the diffusion of mobile phone networks (2G, 3G, & 4G) as a proxy for (general) technology adoption. Thus, by partialling out the effect of lightning strikes on the diffusion of technology, the IV strategy exploits variations in outages induced by lightning strikes. In other words, while the exclusion restriction assumption may not hold unconditionally, the assumption is highly plausible conditional on controls such as mobile network penetration, and spatial and time fixed effects.

In addition to the cross-country analysis, I conduct two country case studies. First, I exploit a unique quasi-natural experiment in Ghana induced by a four year nationwide power ("Dumsor") crisis between 2013 and 2016.[4] The crisis led to severe power rationing in the country. I estimate the impact of the power crisis on employment by exploiting plausibly exogenous variation in exposure to the crisis using a difference-in-difference design. In addition, I present evidence from Nigeria where I rely on household panel data on employment outcomes and quality of electricity supply to estimate the effect of unreliable electricity supply on employment rates using a panel fixed effect design.[5]

Finally, in terms of causal mechanisms, I provide evidence on the intensive and extensive margins. On the intensive margin, I use firm-level data from 10 African countries to evaluate the effect of outages on firm performance and labor demand using the same IV design. On the extensive margin, I evaluate the role of quality of electricity provision on firm entry (and exit) using two approaches. First, I use firm census data from Ethiopia to show how reliability of electricity influences (net) entry of firms using a fixed effect

[4]See https://www.theguardian.com/world/2015/may/17/ghanas-celebrities-lead-protest-marches-against-ongoing-en and https://en.wikipedia.org/wiki/Dumsor

[5]Identification here relies on within household variations in exposure to outages.

estimator. Second, I leverage the "Dumsor" power crisis in Ghana to estimate the effect of unreliable electricity provision on entry of foreign firms using greenfield foreign direct investment (FDI) as a proxy. Specifically, I utilize unique data on greenfield FDI projects from fDiMarkets[6] and the synthetic control method to estimate the effect of the crisis on FDI in the non-energy-and-construction sectors[7] of the Ghanaian economy.

The main finding of the paper is that electricity outages exert a non-trivial negative impact on employment. From the cross-country analysis, I find that outages reduce employment by about 13.5 percentage points (pp). The results of the country case studies in Ghana and Nigeria also show a negative effect of outages on employment that are economically and statistically significant, albeit with relatively low magnitudes: the DID estimates from Ghana suggest that the "Dumsor" power crisis increased unemployment by 4.7 pp, while the fixed effects estimates from Nigeria suggest that outages are associated with a 5.7 pp increase in unemployment. Thus, overall the estimates suggest that outages are associated with a 4.7 pp to 13.5 pp increase in unemployment in the region. Additionally, evidence from the paper suggests that the effects are largely concentrated in employment in non-agricultural sectors and skilled jobs. Employment of unskilled workers are unaffected by outages. The null effect of outages on employment of unskilled workers provides support to the identification strategy in estimating the causal impact of outages on employment as, in practice, we do not expect unskilled tasks or jobs reliant on manual labor to be affected by outages. I also find suggestive evidence that the job losses associated with unreliable electricity provision are largely concentrated in the private sector. Interestingly, employment in the public sector increases with unreliable electricity provision, albeit the level of increase is relatively lower than the job losses in the private sector, hence the overall reduction in employment.

[6]a subsidiary of the Financial Times. See https://www.fdimarkets.com/

[7]The exclusion of FDI to the energy and construction sectors is motivated by two main factors: (i) FDI into the energy sector may increase in direct response to the power crisis, thereby leading to reverse causality; (ii) FDI to the construction sector in Africa is mainly concentrated in the real estate sub-sector which is less reliant on energy. Hence, the power crisis is less likely to affect FDI to the sector.

On potential mechanisms through which electricity shortages affect employment, I document two key findings. First electricity shortages reduce the entry of new firms through a reduction firm density and FDI. Evidence from the Ethiopian firm census data shows that areas with high prevalence of outages have lower number of manufacturing firms operating. Incumbent firms also operate for lower durations during the year, as outages force them to operate below optimal capacity and sometimes shut down production plants during periods of outages. Further, results from a synthetic control method (SCM) estimation of the effect of the "Dumsor" power crisis in Ghana suggest that between 2013 and 2016 (during the crisis), the number of FDI projects to the non-energy-and-construction sectors in the country declined by about 12.3% per annum. High cost of doing business and the unfavorable macroeconomic shocks induced by the crisis are possible reasons for the slump in FDI. As a result, businesses that would have otherwise create jobs were lost.

Secondly, the paper shows that outages also affect the performance of incumbent firms. The results show a negative effect of outages on firm revenue and productivity: for every percent increase in the frequency of outages experienced by firms, sales, sales per worker and value-added per worker decline by 1.2%, 1.3% and 2.3% respectively. Further, I find a negative effect of outages on labor demand, particularly, temporary workers. A percent increase in outage frequency (duration) is associated with a 0.58% (0.32%) reduction in the number of temporary workers hired by firms. The effect on demand for full time workers is also negative albeit statistically insignificant. In addition, the results show a negative and significant effect of outages on total labor cost and labor cost per worker. This provides suggestive evidence that firms perhaps respond to the declining revenue as a result of outages by reducing wages. Overall, the findings of the paper suggest that the negative of outages on firm entry and performance of incumbent firms are plausible channels through which outages affect employment.

This paper offers two main contributions to the literature. First, to the best of my knowledge, this paper presents the first causal evidence on how the provision of unreliable electricity services in the developing world contributes to unemployment in the region. Unlike the existing studies (see for example Allcott et al., 2016; Chakravorty et al., 2014; Alam, 2013; Steinbuks and Foster, 2010; Fisher-Vanden et al., 2015; Reinikka and Svensson, 2002), this paper moves beyond quantification of the level of impact of electricity shortages on firm productivity, to examine the implications on employment. Allcott et al. (2016), for instance, offer evidence on the effects of electricity shortages on the performance of Indian firms. They show that electricity shortages reduce firm revenue by 5 to 10 percent albeit the productivity losses are marginal. In China, evidence from Fisher-Vanden et al. (2015) indicate that firms respond to electricity shortages by re-optimizing input use. Notably, the paper reveals that in spite of the high cost of outsourcing, Chinese manufacturing firms outsource their production in order to mitigate the high productivity losses associated with outages. In the African context, Cole et al. (2018) and Abeberese et al. (2021) also provide evidence of a negative effect of outages on firm performance. What is absent so far, in the literature, is the labor market implications of the impact of outages on the industrial sector. The results from this paper therefore contribute significantly to filling this gap in the literature.

Secondly, this paper brings new knowledge to the strand of the literature on the impact of distortions in business climate on firms (Restuccia and Rogerson, 2008; Hsieh and Klenow, 2009; Garicano et al., 2016) by showing the implications of the distortions induced by outages on entry of new firms. Restuccia and Rogerson (2008) for instance assert that distortions in the business environment affect productivity and resource allocation. As a result, efficient firms tend to produce too little and employ few workers. These distortions have also been shown to account for the productivity gaps between the advanced and developing economies (Hsieh and Klenow, 2009). Evidence from Abeberese (2017) also indicate that high energy cost constrains the ability and incentives of firms to move into high productive energy intensive industries. Apart from providing evidence on the effects of outages on performance of incumbent firms, findings from the paper indicate that outages affect the entry of new firms as well by reducing the incentives of investors to invest in markets riddled with unreliable power supply.

The remainder of this paper is structured as follows. Section 2 presents the theoretical underpinnings on the effects of electrification on employment and job creation. Details on data and construction of key variables are presented in Section 3. The identification strategy and results of the paper are outlined and discussed in Section 4. I explore potential mechanisms in Section 5. The paper concludes in Section 6 with a summary of the key findings and implications for policy.

2 Conceptual Framework

Technology shocks such as electrification affect economic outcomes in diverse ways. First, electricity affects the nature of home production (Lewis, 2014). Through appliance use, electricity increases labor productivity in home production such as cooking, washing, ironing, etc., thereby reducing total time spent on home activities and freeing up labor for participation in the labor market (Greenwood et al., 2005; Ramey and Francis, 2009; Coen-Pirani et al., 2010; Dinkelman, 2011; Lewis, 2014; Akpandjar and Kitchens, 2017). It also creates an endowment effect through the demand for market goods (iron, fans, fridges, etc) whose utilization has been made possible by the presence of electricity (Dinkelman, 2011). The need for income by households to 'effectively' demand these market goods pushes them to supply more labor into the market (Dinkelman, 2011; Lewis, 2014).

Electrification also improves the productivity of local economies. Extending electricity services to communities enables the adoption and utilization of modern technology (such as irrigation) to improve labor productivity (Assunção et al., 2014; Lewis and Severnini, 2014). For instance, electrification in farming communities can increase mechanization and enhance irrigation schemes to improve agricultural productivity (Assunção et al., 2014; Lewis and Severnini, 2014). Access to electricity can also spur technology adoption among local (cottage) industries thereby boosting productivity and possible spillover effects on employment and wages (Fried and Lagakos, 2021).

Further, electrification like most technology shocks offer opportunities for the creation of new businesses and induce structural change (Fried and Lagakos, 2021). Access to electricity can foster the creation of new jobs as it spurs prospective entrepreneurs to take advantage of the enabling conditions the infrastructure provision offers. For instance in many developing economies where the informal sector dominates, access to electricity can enable households to set up small firms that produce intermediate or final goods (and services) for the market. Additionally, appliance use and modernization of agriculture and local industries through the use of electricity can shift employment into skilled non-agricultural employment, thereby reducing the share of labor employed in agriculture. A booming non-agricultural sector increases demand for labor and thus reduces out-migration in electrified communities, while attracting labor from neighboring localities to participate in the booming economy (Fried and Lagakos, 2021). Implicit in the above is the assumption that electricity services are stable and reliable. Meanwhile, electricity outages are pervasive in many developing countries thereby constraining the realization of the full impact of electrification. In this section, I outline three channels through which unreliable electricity provision affect job creation.

First, the quality of electricity supply can affect firm entry and exit. Persistent outages signal high production cost and uncertainties in the business climate thereby reducing the incentive(s) of potential entrepreneurs (investors) in establishing (investing in) businesses. For instance, persistent outages may reduce foreign direct investment in non-energy intensive sectors such as manufacturing due to the associated effects of unreliable power supply on cost of doing business.[8] A negative effect of outages on investments into

[8]Investment in the energy sector may however increase as the outages may be associated with factors such as capacity constraints or underdevelopment of the power sector, hence the potential for higher returns on investment(s) in the sector.

greenfield (new) projects[9] could reduce firm entry and hence job creation. In addition, firms may respond to unreliable electricity provision by relocating to regions (countries) with reliable access to electricity or shut down production to avoid investment losses.[10] Thus, pervasive outages constrain expansion of the industrial and service sectors with direct and indirect impacts on job creation.

The second channel relates to the effect on firm performance. A plethora of evidence suggest that electricity shortages impose significant losses in productivity and profitability (Fisher-Vanden et al., 2015; Allcott et al., 2016; Cole et al., 2018). These impacts have labor market implications: firms respond to these adverse productivity shocks by reducing variable cost through job cuts or reducing wages. In addition, some firms respond to electricity supply uncertainties by either substituting materials for energy inputs or outsourcing intermediate production to external firms (Fisher-Vanden et al., 2015). These strategies, particularly, outsourcing to external firms often result in layoffs.

Finally, outages can affect trade and export competitiveness of firms. Unplanned outages distort production schedules of firms reliant on grid supply of electricity thereby affecting their ability to adequately meet the needs of their (domestic/international) clients. Firms reliant on in-house electricity generation also face high energy cost, due to the high cost per kWh of in-house generation relative to grid supply (Steinbuks and Foster, 2010). High energy cost increases production cost and output prices thereby affecting the competitiveness of firms on export markets. Hence persistent outages could have negative implications on employment in a country with a buoyant export sector as exporting firms may struggle to survive.

In this paper, I provide evidence on the effects of electricity outages on firm performance, FDI, and firm entry as potential pathways through which outages affect job cre-

[9]Investments in brownfield (existing) projects could also be affected by outages particularly in the event of prolonged power crisis in a country

[10]Under the assumption of free mobility of labor and capital, firms may choose to relocate to areas with reliable supply. However, the cost of relocation is non-trivial.

ation in Africa.

3 Data

3.1 Individual and Household Data

3.1.1 Afrobarometer Survey

The Afrobarometer survey is a nationally representative survey of public attitudes on democracy, governance, economic conditions, and access to basic social amenities in over 35 African countries. The survey uses a two-stage stratified sampling strategy and focuses on individuals above the age of 18. Data from rounds 6 (2014-15) and 7 (2016-18) of the Afrobarometer are used for the analysis. The dataset is geo-referenced at the community level, making it possible to spatially match it with other datasets. Data from 25 Sub-Saharan African (SSA) countries are used in this paper[11].

I use data on employment status of individual(s), quality of electricity supply, socioeconomic attributes of the individual and their respective households, and community characteristics as well. Employment status is measured based on responses to the question: "Do you have a job that pays a cash income?". Thus employment is defined as equal to 1 if a respondent reports having a cash-paying job, and 0 for a respondent without a cash-paying job but actively looking for a job.[12] In addition, using the information on their occupational history, respondents were classified into skilled vs unskilled workers, and agric vs non-agric sector employees. Quality of electricity supply is measured from the responses of households with electricity connection to the question "how often is the electricity actually available?". Here the quality of electricity supply is classified

[11]Including Botswana, Burkina Faso, Cameroon, Côte d'Ivoire, Cabo Verde, Gabon, Gambia, Ghana, Guinea, Lesotho, Liberia, Madagascar, Malawi, Mauritius, Mali, Mozambique, Namibia, Niger, Nigeria, Senegal, Sierra Leone, South Africa, Swaziland, Zambia, and Zimbabwe

[12]In essence, the employment variable is returned missing for respondents that responded "No (not looking)" to the question.

as reliable if a (connected) household receives electricity supply always and unreliable if otherwise. Using these data, I compute a measure of reliability in a community based on the share of electrified households in the primary sampling unit that have reliable access to electricity. Specifically, two main measures of reliability are computed: first, a dummy variable (outages in community) equal to 1 if more than 50 percent of connected households in the primary sampling unit (PSU) do not have access to reliable electricity; and second, the share of connected households without reliable access to electricity (outages in community % HH).

3.1.2 Living Standards and Measurement Surveys

Household survey data from the Ghana Living Standards Survey (GLSS) and Nigeria General Household Survey (GHS) are used to supplement the analysis in the country-case studies. The GLSS is a nationally representative repeated cross-sectional data. Five rounds of the GLSS data between 1998 and 2017 are used. The GHS on the other hand is a nationally representative household panel data from Nigeria. The analysis relies on three waves of the GHS panel data surveyed between 2011 and 2016. Employment status of respondents is measured in slightly different ways in the two surveys. In the case of the GLSS, individuals are asked about their employment activities over the last 12 months, while in the case of GHS, individuals are asked about their employment activities within the past 7 days preceding the survey.

3.2 Firm Data

3.2.1 World Bank Enterprise Surveys

The World Bank Enterprise Surveys (WBES) dataset is a global firm survey that undertakes face-to-face interviews with top managers and business owners in about 145 countries. The survey collects data on several issues relating to firm attributes, access to infrastructure, constraints to doing business, competition, among others. The survey uses the two-stage stratified random sampling strategy. I use the global standardized version of the dataset which uses a standardized sampling strategy and questionnaire. All monetary data are converted into 2009 USD prices using the GDP deflator and exchange rates for the respective countries. The final dataset, therefore, is repeated cross-section data of firms in 10 SSA countries[13] surveyed between 2006 and 2018. To account for these time and country variations in the dataset, year and country fixed effects are applied respectively in the estimation.

The dataset reports annual revenue and cost of inputs rather than physical measures of outputs and inputs. Productivity in this paper is measured using two indicators: value added per worker and sales per worker. Value added is computed as total sales revenue less the cost of raw materials and intermediate inputs (Hjort and Poulsen, 2019). Additional firm outcomes used paper include number of employees (full-time, temporary), total labor cost, and labor cost per worker. The age of the firm and foreign/domestic ownership status of firms are also included in the data.

Two measures of self-reported power outage intensity are explored in the firm analysis: (i) outage frequency measured as the average number of times a firm experienced power outages in a typical month; and (ii) the number of hours without electricity in a typical month, measured by the product of the frequency and average duration of outages in a typical month. Arguably, these self-reported measures of outage intensity, are not without biases. However, administrative data on outage intensity are virtually non-existent in many African countries, thus making the self-reported measures the best possible means of measuring outage intensity. Additionally, given the prevalence and regular nature of power cuts in the study area, the extent of bias associated with recall, if any, will be minimal, other things being equal.

Finally, the GPS location of firms in the WBES dataset is not publicly available due

[13] Benin, Côte d'Ivoire, Congo DR, Ghana, Malawi, Mauritius, Mozambique, Sierra Leone, Togo, Zambia

to privacy concerns. To overcome this challenge, I geo-reference the city/towns in which firms in the dataset are located and match them with other spatial datasets.

3.2.2 Ethiopian Large and Medium Manufacturing and Electricity Industries Survey

The large and medium manufacturing and electricity industries survey (LMMIS) is an annual census of all large and medium manufacturing firms with at least ten employees and rely on electricity for production in Ethiopia. The data is collected by the Central Statistical Authority (CSA), and all firms that meet the criteria are mandated by law to comply with the requirements of the CSA and participate in the survey (Essers et al., 2021). As a result, the LMMIS captures the universe of all formal large and medium scale manufacturing entities in the country (Essers et al., 2021). The main limitation of the data, however, is that it mainly captures formal firms thus excluding firms in the informal sector.

The data provides information on inputs, outputs, investments and capital expenditure, capacity utilization, duration of operation, as well as the main issues confronting firms. Unlike the WBES, the LMMIS data does not have explicit questions on the intensity of outages faced by firms. Instead, the survey asks firms to list the major issues (including electricity outages) confronting them and in some instances whether these issues affected their ability to operate fully during the calender year. I leverage these responses and measure firms' exposure to unreliable electricity supply based on whether firms cite outages as a major issue confronting their operation. Specifically, I construct a dummy variable equal to 1 if a firm indicates electricity outages as a major issue either: (i) currently facing the firm; (ii) responsible for not operating at full capacity; or (iii) responsible for not operating all year round; and 0 if otherwise. Data from 2011 to 2017 are used in this paper.

Further, using this census data, I compute for each district (Woreda[14]), the number of firms operating in a given year, and firm density (number of firms per 1000 people[15]) for

[14] Third administrative region in Ethiopia

[15] Subnational population data on Ethiopia were obtained from https://data.humdata.org/dataset/ethiopia-population-data-_-admin-level-0-3

each year. These measures provide insights into the distribution of manufacturing firms across space and time in the country. Information on the number of months in the year for which the firm operated is also used in the analysis.

3.3 FDI Data

To further understand the effects of outages on entry of (foreign) firms, I use a unique dataset on greenfield foreign direct investment projects. These data are obtained from fDi Markets,[16] a subsidiary of the Financial Times (FT) Group. fDi Markets database tracks cross-border investment projects around the world since 2003. The database is primarily used by agencies such as the World Bank, the Economist Intelligence Unit and UNCTAD in monitoring cross-border investments. It provides granular data on the project's primary sector, sub-sector, country (city) of origin, destination country (city), investment size, etc. For the purpose of this paper, FDI project data on 23 emerging markets in Africa, Latin American and Caribbean, and Asia[17] between 2007 and 2017 focusing solely on investment in sectors excluding energy and construction sectors.

3.4 Lightning Data

Lightning intensity is used as an instrument for electricity outages. However granular data lightning occurrence in Africa and many developing countries is a challenge. Available data on lightning activities in developing countries are mainly satellite-based measures of lightning intensity which come from NASA's LIS/OTD Gridded Lightning Climatology Dataset.[18]. This dataset is cross-sectional and reports the average number of lightning strikes between 1995 and 2010 and is available at a relatively low spatial resolution of

[16] https://www.fdimarkets.com/

[17] Cambodia, Ghana, Guatemala, Honduras, India, Jamaica, Kenya, Morocco, Mexico, Myanmar, Mauritius, Namibia, Nicaragua, Pakistan, Philippines, Senegal, South Africa, Uganda, Uruguay, Uzbekistan, Vietnam, Zambia, Zimbabwe

[18] https://ghrc.nsstc.nasa.gov/uso/ds_docs/lis_climatology/LISOTD_climatology_dataset.html This is arguably the most widely used measure of lightning intensity in the literature

$0.5° \times 0.5°$. The lack of temporal variation due to the cross-sectional nature of the dataset coupled with relative low spatial resolution $(0.5° \times 0.5°)$ poses a challenge to the use of this dataset as an instrument to causally estimate the effects of outages.

Recent scientific literature however shows that observed lightning intensity is proportional to the product of convective available potential energy[19] (CAPE) and precipitation rate (i.e., the amount of precipitation that would cover a given area (m^2) per second) (Romps et al., 2014; Dewan et al., 2018). In an attempt to find granular data on lightning intensity and aid future projections of lightning intensity associated with climate change, Romps et al. (2014) proposed a proxy for measuring lightning intensity:

$$F = \frac{\eta}{E} \times CAPE \times P \tag{1}$$

where F is the lightning flash rate per area $(m^{-2}s^{-1})$, while CAPE (J kg^{-1}) and P(kg $m^{-2}s^{-1}$) represent the convective available potential energy and precipitation rate respectively. η/E, a constant of proportionality, is the ratio of the conversion efficiency factor (η) and the energy discharge (in joules) per flash (E).[20] Romps et al. (2014) validate this methodology by showing that $CAPE \times P$ explains about 77% of the variance in actual lightning flash rate in continental United States. Dewan et al. (2018) also using data from Bangladesh show a significant correlation between actual lightning strikes and $CAPE \times P$ with the latter explaining about 89% of the variance in the former on a monthly time scale.

Therefore, following Romps et al. (2014) and Dewan et al. (2018), I use $CAPE \times P$ as a proxy for lightning intensity. Specifically, using time series data on CAPE and precipitation rate from the ERA5 Global Reanalysis Database by the Copernicus Climate Change Service[21], I compute $CAPE \times P$ at a $0.25° \times 0.25°$ grid-cell level and use it as an instrument

[19] This measures the amount of energy a parcel of air would gain if raised to a specific height in the atmosphere. See: https://study.com/academy/lesson/convective-available-potential-energy-cape-definition-use-in-forecasting.html

[20] See Romps et al. (2014) for details.

[21] https://cds.climate.copernicus.eu/cdsapp#!/home

for the level of electricity outages in the respective years. To demonstrate that this proxy correlates with actual lightning intensity in the African context, I use data on lightning flash rate from NASA's OTD/LIS satellite and correlate it with the proxy ($CAPE \times P$) as shown in Figure A1, and Figure A2 in the online appendix. The scatter plot in Figure A1 reveals a high r-square: $CAPE \times P$ explains about 77% of the variations in lightning intensity in Africa, thus confirming the earlier findings of Romps et al. (2014). Figure A2 in the online appendix also shows a high spatial correlation between the actual lightning flash rate and the proxy.

In addition, data on mean annual temperature and precipitation from the ERA5 Global Reanalysis Database[22] are used in the analysis. Summary statistics are presented in Table A1 in the appendix.

4 Empirical Strategy and Results

4.1 Identification Strategy

Empirical estimation of the causal impact of electricity outages on outcomes such as employment and firm productivity is often beset with methodological challenges. Notable among them is the issue of endogeneity resulting from the potential correlation between outage intensity and (observable and unobservable) factors that (in)directly influence these outcomes. In other words, any assumption that variations in outage intensity are orthogonal to economic outcomes such as employment and firm productivity is unlikely to be valid. For instance, firm location, industry composition, and the prevailing economic and political conditions in a country can influence both outage intensity and the performance of firms. Also, regions with high unemployment and hence low income are more likely to suffer outages possibly due to the non-payment of electricity services leading

[22] https://cds.climate.copernicus.eu/cdsapp#!/home

to the vicious cycle of outages and non-payment of electricity bills (Dzansi et al., 2018). Additionally, self-reported measures of outage intensity are plausibly measured with error, hence the possibility of a downward bias (attenuation bias) in the impact from OLS estimation cannot be ignored (Allcott et al., 2016). To address these issues, I utilize the instrumental variable approach and exploit spatial and time variations in lightning intensity as an instrument for power outages.

Lightning is a major cause of power outages around the world particularly within the tropics where thunderstorm activities are prevalent (Andersen et al., 2011, 2012; Andersen and Dalgaard, 2013). Lightning strikes contain about a billion volts of electricity; therefore when it strikes a transmission line or transformer, it induces voltage surge, thereby destroying the transmission lines and equipments[23] and curtailing the flow of electricity. Electrical infrastructure destroyed by lightning induced voltage spikes and dips, could take several days to be repaired and often entail high cost of replacement. As a result, affected communities often go several days without electricity. In South Africa for instance, lightning is estimated to account for nearly 65% of all over-voltage damages to electrical transmission network[24], with strikes within 40 meters of a transmission (distribution) line causing significant damages (Andersen and Dalgaard, 2013). Similar effects have been recorded in Swaziland[25] (Mswane and Gaunt, 2005), Nigeria[26] and Ghana[27]. In the United States, lightning activities account for about a third of all incidence of power outages (Chisholm and Cummins, 2006). Moreover, the fact that lightning activities are natural phenomena, it induces random variations in the incidence and intensity of outages across space and time conditional on locational and climatic characteristics. Consequently, lightning strikes have increasingly been used as an instrument for the quality of electric-

[23] http://www.liveline.co.za/lightning-stats.php

[24] http://www.liveline.co.za/lightning-stats.php

[25] Lightning accounts for about 50% of outages incidence in the country (Mswane and Gaunt, 2005)

[26] Adepitan and Oladiran (2012) estimates that lightning accounts for nearly 10% of random electricity outages experienced in Ijebu province.

[27] http://www.ghanaweb.com/GhanaHomePage/NewsArchive/Lighting-cuts-electricity-to-Sissala-East-district-453319

ity and diffusion of electric-powered technologies in the economics literature (Andersen et al., 2011, 2012; Andersen and Dalgaard, 2013; Manacorda and Tesei, 2020; Guriev et al., 2020).

Therefore, I estimate the effects of electricity outages on employment using the IV framework with the baseline regression specified as follows:
IV first-stage:

$$Outages_{jct} = \phi \times Lightning_{jct} + \mathbf{X'_{ijct}}\alpha_1 + \theta_c + \delta_t + \mu_{ijct} \tag{2}$$

IV second-stage:

$$Y_{ijct} = \beta \times \widehat{Outages}_{jct} + \mathbf{X'_{ijct}}\alpha_2 + \theta_c + \delta_t + \epsilon_{ijct} \tag{3}$$

where Y_{ijct} is the outcome variable for individual i living in community j, country c at time t. $Outages_{jct}$ is a measure of (average) electricity outage intensity in the community. Two measures of outage intensity are explored here: first, an indicator variable equal 1 if more than 50% of households (respondents) interviewed in the primary sampling unit (PSU) receive poor quality electricity services[28] in the relevant period and 0 if otherwise; Second, the share of households who experience poor (quality) electricity services. The communal measure of outage intensity is preferred to household measure as the former captures, to a large extent, the general quality of electricity services in the community relative to the latter. More so, since most individuals are usually employed outside their home[29], a household measure of outage intensity may not suffice. Additional estimations are done using measures of outage intensity at the district level to account for the effects of outages on employment of people who work outside their communities. The results

[28]Poor quality electricity is defined as either having electricity occasionally, about half of the time or most of the time. Electricity supply is defined as of high quality if a connected household receives electricity all the time. In Section 4.2.3, I explore alternative estimations by redefining our measure of electricity reliability to include households who receive electricity most of the time and always.

[29]Even for individuals employed in household enterprises, the enterprises may be located outside the home (e.g. in market or trading centers). Hence the average quality of electricity supply in the community suffices as a good measure of than the quality of supply reported at the household level.

remain robust to the measure of outages. $\mathbf{X_{ijct}}$ is a vector of individual controls including age and gender. I also control for temperature and precipitation to absorb the potential channels through which the instrument (lightning) could affect the outcome variable. θ_c and δ_t represent respectively, country and year fixed effects to control for time-invariant characteristics as well as time-varying correlates of the outcome variable. $Lightning_{jct}$ represents the lightning intensity in community j at time t. As highlighted in Section 3.4, this is proxied by $CAPE_{jct} \times P_{jct}$.

The exclusion restriction assumption requires other than through outages, unemployment rates should not vary over time across locations depending on the average lightning intensity. In other words, lightning intensity is not correlated with the outcome variable via channels other than through outages. While this assumption is not directly testable, I identify two possible channels through which this assumption may be violated. First, given that lightning strikes are associated with rainfall, and rainfall also being a driver of economic activities particularly in developing countries where agriculture is the main stay, lightning could influence employment outcomes via rainfall. To mitigate this concern, I control for local climate conditions such as temperature and precipitation (rainfall) directly in the regression to absorb this potential channel. Secondly, lightning can directly (indirectly) also influence the diffusion of modern technologies such as mobile phones. As shown by Manacorda and Tesei (2020) and Guriev et al. (2020), areas with high lightning intensities often tend to have low penetration of digital technologies such as mobile phones as voltage surges often associated with lightning causes damages to electrical components of digital infrastructure. Thus to the extent that access to digital infrastructure (technology in general) matter for productivity and employment outcomes, lightning activities may possibly influence employment through uptake of these technologies. Again, to mitigate this concern, I control for the extent of technology diffusion in the respective communities (cities) using mobile phone (2G/3G/4G[30]) coverage rate as a proxy. Thus

[30]second, third and fourth generation mobile technologies

conditional on the technology diffusion, climate indicators, and the other controls including location and time fixed effects, I argue that lightning intensity influence employment outcomes only through its effect on electricity outages. μ_{ijct} and ϵ_{ijct} represent respectively, the error terms for the first and second-stage equations. Standard errors are clustered at community level (primary sampling unit).

The main parameter of interest, β measures the causal effect of electricity outages on the outcome variable. Therefore conditional on the instrument validity, $\hat{\beta}_{IV}$ recovers the local average treatment effect (LATE) of electricity outages on the outcome variable(s).

4.2 Baseline Results

This section presents the baseline results on the effect of outages on employment using the Afrobarometer dataset from several African countries.

4.2.1 First-Stage IV Regression

Table 1 presents the results of the first-stage regressions which estimate the relationship between the lightning intensity and our measures of outages: whether a community experiences outages (columns 1-2) and the share of households in a community (columns 3-4) experiencing outages.

The results show a positive association between lightning intensity and outages. In column 2 for instance, I find that a percent increase in lightning intensity is associated with a 12 percentage point (pp) increase in the probability of a community experiencing outages. Similarly in column 4, a percent increase in lightning intensity is associated with a 9 pp increase in the share of households experiencing outages. The strength of the instrument is relatively high as the first-stage F-statistic (Fstat) exceeds the conventional benchmark of 10 (Stock and Yogo, 2005) in all specifications.

To complement the results in Table 1, Figure 1 presents a binscatter plot relationship between lightning intensity and the two measures of outages. The plot confirms the (strong) positive association between outages and lightning activities.

4.2.2 Main IV Results

Table 2, reports the OLS, second-stage IV and reduced formed estimates. I estimate two variant specifications by alternating between survey year and round[31] fixed effects. Starting with OLS estimates column 1, the results show a negative association between exposure to electricity outages and employment outcomes. For instance, in column 2, living in a community with outages is associated with an increase in the probability of being unemployed by 2 pp. Likewise, the effect is negative and statistically significant in relation to non-agric employment and unskilled jobs. The relationship between outages and employment of skilled and agric-sector workers are statistically insignificant. While these estimates are non-causal they provide suggestive evidence that outages are negatively associated with lower employment outcomes.

Turning to the IV estimates, the results also show that outages indeed have negative effects on employment, albeit the IV estimates are relatively large compared to the OLS estimates.[32] In column 2 for instance, I find that living in a community that experiences frequent electricity outages reduces the probability of employment by 13.5 pp. Interestingly, it appears that these effects are driven entirely by the effect on employment in non-agric sectors (column 3-4) as the effect on the probability of employment in agric related jobs is almost zero (5-6) and statistically insignificant. There are at least two candidate reasons behind the null effect of outages on agric-related employment: first, the agric sector in many African countries have low technology intensity, as a result, the potential effect of electricity outages on production in the sector is minimal. Secondly, given the definition of employment as measured in the Afrobarometer as being having a "cash paid" job,

[31] The differences arise because survey rounds often overlap calender years across countries

[32] This suggest the possibility of a downward bias in the OLS estimates plausibly due measurement errors in the measure of outages Allcott et al. (2016).

only 6.1% of the individuals in the sample with such jobs are employed in the agric sector. In other words the sample of employed individuals in the sample are heavily skewed ($\approx$ 94%) towards the non-agric sectors which incidentally are more energy intensive than the agric sector. Hence, it is unsurprising to see a null effect of outages on employment in the agriculture sector.

How does the employment effect of outages vary between skilled and unskilled workers? To address this question, I split the sample into skilled and unskilled workers and estimate the baseline equations. In columns 7-8, the results show a negative and statistically significant negative effect of outages on employment of skilled workers. Outages reduce the probability of employment of skilled workers by 19 pp (column 8). Interestingly, the effect of outages on employment of unskilled workers are statistically insignificant albeit negative. The null effect of outages on unskilled jobs provides a good placebo test to the validity of the IV design, showing that the IV regressions are only picking up variations in lightning intensity that affect electricity outages as we do not expect outages to significantly alter the labor market outcomes of people in low skilled occupations given the low energy intensity of such occupations. Thus, if the instrument is picking-up other effects such as the diffusion of digital technologies like mobile phones, one would expect to see robust negative effects on employment outcomes of both skilled and unskilled persons as well as agriculture-sector jobs as mobile phones have been shown to be positively correlated with household welfare in developing countries (Bahia et al., 2020; Masaki et al., 2020).

Still, in Table 2, I present the reduced-form estimates showing the relationship between lightning intensity and the probability of employment. Unlike the IV estimates, the reduced-form estimates do not require the exclusion restriction assumption to hold. The results show a negative association between lightning intensity and employment outcomes: an increase in lightning intensity is associated with a lower probability of employment, particularly, in the non-agric sectors and skilled jobs.

Taken together, the results from the table suggest that while outages constrain employment, skilled workers are disproportionately affected. This is plausibly due to the fact electricity is a key input in the production process, and thus essential for most skilled workers in undertaking their activities at the workplace. Hence, unreliable electricity provision has negative consequences on the creation of skilled jobs in Africa.

4.2.3 Sensitivity analysis and additional results

In this section, I present additional analyses of the effects of outages across heterogeneous groups and also explore the robustness of the baseline results to measure of exposure to outages.

Private vs Public Sector Jobs: In addition to the effects of outages on employment across skill levels, and agric vs non-agric sector jobs, I also explore the effects across employment in private vs public sectors (see Table A2 in the online appendix). This distinction is important for at least two reasons. First, as profit maximizers, private firms are likely to lay off workers when faced with challenges such as an energy crisis which increases their production costs and lowers profits. However, public sector firms may be able to keep workers on their payroll even in times of crisis, for instance, due to their ability to receive government subsidies for job preservation. Secondly, in many developing countries, the public sector remains the largest employer of formal sector workers[33] and job cuts in this sector come with political costs.[34] In some cases, public sector jobs are likely to increase during periods of crisis as a way to reduce unemployment.[35]

Table A2 (online appendix) presents the results on the effects of outages on the probability of employment: all sectors (columns 1-2), private sector (columns 3-8), and public sector (9-10). In column 4, the IV estimates suggest that outages have a substantial nega-

[33] https://blogs.worldbank.org/arabvoices/governance-and-public-sector-employment-middle-east-and-north-africa
[34] https://www.imf.org/external/pubs/ft/fandd/1998/06/lienert.htm
[35] https://www.imf.org/external/pubs/ft/fandd/1998/06/lienert.htm

tive effect ($\approx$ 30 pp) on the probability of employment in the private sector (i.e., working for a private firm or self-employment). However, this effect largely pertains to employment by private firms, as there is no effect on self-employment. Interestingly, contrary to the negative effect on employment by private firms, the effect on being employed in the public sector (column 10) is positive and sizeable ($\approx$ 15 pp). This is plausibly suggestive of the role of state-owned enterprises in job preservation in developing countries. Juxtaposing the results in columns 3-8 with 9-10, one can conclude the baseline effects in columns 1-2 are likely the overall net effects of outages on employment.

Effects Across Gender: In Table A3, I also explore the employment effects of outages across gender, and do not find any consistent evidence of significant gender differences in the impact. In other words, outages reduce the employment outcomes of workers irrespective of their gender.

Measurement of outages: In the baseline analysis, outage is defined as an indicator variable equal to 1 if at least 50% of respondents with electricity connection in the community (PSU) report having unreliable supply of electricity and 0 if otherwise. To test the sensitivity of the analysis to this measure, I explore two approaches.

First I define variant measures of the outage dummy by alternating the threshold of the (minimum) share of respondents with unreliable supply of electricity. Specifically, I define additional outage dummy variables coded 1 if at least 10%, 20%, 30%, 40%,..., 90% of respondents with electricity connection report having unreliable supply of electricity and 0 if otherwise. Using these dummies, I estimate separate regressions using the baseline specifications to assess the sensitivity of the point estimates to these measures. The results in Figure A3 in the online appendix show robust negative effects of outages on employment rates. The respective estimates for the dummy variables between the 10% and 70% minimum thresholds are relatively stable, negative and statistically significant at

95% confidence interval. The corresponding estimates for the outage dummies based on the 80% and 90% minimum thresholds are however relatively large and significant only at 90% confidence interval.

As a second strategy, I estimate a variant model using the share of respondents experiencing unreliable electricity supply instead of using the discrete measurement of outages. Results are shown in Table A4 in the online appendix. Once again, the results are qualitatively and quantitatively similar to the baseline results that outages have economically and statistically significant negative effects on the probability of employment.

Exposure to Outages at the District Level: A possible critique of the above analysis is that outages at the community level may not capture the full impact of exposure to unreliable electricity supply, particularly for individuals who work outside their communities. To address this concern, I compute a variant measure of exposure to outages using the share of households in a district (second-level administrative region) experiencing with an unreliable supply of electricity. Essentially, I compute a dummy variable "Electricity Outages in District (0/1)" defined as equal to 1 if more than half of respondents in the district experience outages and 0 if otherwise. Using this measure, I replicate the baseline estimation in equations (2) and (3) to assess the effects of outages at the district level on the probability of employment.[36] The corresponding first and second-stage IV results are shown in Tables A5 and A6 in the appendix respectively. Once again, the IV estimates in Tables A6 are qualitatively and quantitatively similar to the baseline results in Tables 2. This provides an additional assurance that the results are not driven by measurement errors in the outage measure.

Role of Electrification Rates in Measurement of Outage Intensity: Given that our mea-

[36] Accordingly the instrument used here is the log of the average lightning intensity in the district. Standard errors are clustered at the district level.

sure of outages at the community level is conditional on the share of households with electricity connectivity, a potential concern is that the estimated effect of outages on employment could be picking-up the effects of electrification, rather than the "pure effect" of outages. Admittedly, even if this is the case, this could potentially imply that our estimates are lower bound, given the evidence in prior literature showing that access to electricity is associated with increased employment (Dinkelman, 2011). Nonetheless, I leverage two strategies to show that the baseline results are not driven by differences in electrification rates. First, in Table A7, I explicitly control for electricity access by including a dummy variable set equal to 1 if the electricity access rate in the community is above the median and 0 if otherwise.[37] The results remain robust, showing that indeed exposure to outages is associated with a decline in employment. Second, I restrict the sample to communities with universal access to electricity. Intuitively, by so doing, I net out the effects arising from differences in electrification rates across communities. Once again, the results in Table A8 confirm that outages are associated with a decline in employment.

Role of Outliers: An additional concern relates to the sensitivity of the first-stage relationship to the inclusion or exclusion of countries. In other words, is there a particular set of countries for which the lightning-outage relationship holds? For instance, is it that countries with low grid quality are the ones where outages are sensitive to lightning strikes? And if yes, is unemployment peculiar to such countries? The sensitivity of our first-stage results to the omission of countries could pose questions to the IV results. To this end, I perform a "leave-one-out" exercise by estimating the first-stage equation while systematically excluding each of the sample countries one at a time. The results in Figure A4 suggest that our results are not driven by the inclusion/omission of specific countries, as the results remain largely stable to the sample composition.

[37] It is important to emphasize that given the relationship between electricity connection and outages, controlling for the degree of electrification could lead to the problem of "bad controls" (Angrist and Pischke, 2009)

4.3 Country Case Studies

In this section, I undertake a deep-dive analysis of the effects of outages on employment by presenting two country case studies: Ghana and Nigeria

4.3.1 Ghana: The "Dumsor" Power Crisis (2012-2016)

Between 2012(Q4) and 2016, Ghana faced with the worst power crisis in the country's history. The crisis was so severe that it led to massive demonstrations by citizens protesting[38] against the government's inability to provide reliable power. The incessant power cuts during the period was nick-named "*Dumsor*[39]" to wit "*off and on*".

To manage the crisis, the Electricity Company of Ghana[40] (ECG) implemented a power rationing program where available power were rationed among communities using a schedule published in the newspapers (see Figure 2). At the height of the crisis, consumers were guaranteed only 12-13 hours of electricity for every 36 hour period.

The effect of the crisis on firms and industry was severe leading to significant productivity losses, particularly, among small-and-medium scale enterprises, particularly those without access to in-house generators as a backup option (Abeberese et al., 2021). To what extent did this crisis affect employment? The power crisis in Ghana provides a unique quasi-natural experiment to examine the effect of electricity outages on employment. To this end, I leverage household survey data between 1998 and 2017 and exploit plausibly exogenous variations in exposure to power crises to estimate the effect of outages on employment using a difference-in-difference (DiD) design (Kuka et al., 2020; Verner and Gyöngyösi, 2020): Essentially, I exploit differences in dependence of local economies on electricity and estimate the differences in employment outcomes between high and low electricity dependent districts before and after the crisis using the specification in equa-

[38] https://www.theguardian.com/world/2015/may/17/ghanas-celebrities-lead-protest-marches-against-ongoing-energy
Accessed: December 2020

[39] https://en.wikipedia.org/wiki/Dumsor

[40] the main distributor

tion 4

$$Y_{idt} = \phi \times HighExposure_d \times PowerCrisis_t + \mathbf{X'_{idt}}\alpha + \gamma W_d \times t + \theta_d + \delta_t + \lambda_{YOB} + \epsilon_{ijct} \quad (4)$$

where Y_{idt} is the employment status of individual i, in district d , surveyed in year t. $HighExposure$ is a measure of a district's dependence on electricity before the crisis. It is defined as an indicator variable equal to 1 if electricity access rate in the district at the baseline[41] is higher than the median access rate in the country and 0 if otherwise. $PowerCrisis$ is an indicator variable equal to 1 for the period between 2013 and 2016 when the power crisis was at its peak. $\mathbf{X_{idt}}$ is a vector of individual controls. I also control for trends in observable determinants of local economic development by including district level characteristics (during the baseline) interacted with linear time trend. District and year fixed effects are represented by θ_d and δ_t respectively. I also include birth-year fixed effects (λ_{YOB}) to account for age-cohort effects. Standard errors are clustered at district level.

The coefficient of the interaction between $HighExposure$ and $PowerCrisis$ represented by, ϕ, measures the difference in employment outcomes between high and low access (electricity dependent) districts in the crisis and non-crisis periods. The intuition behind the identification strategy is that economic activities in districts with high electricity access are plausibly highly reliant (dependent) on electricity for economic activities relative to low access districts. As a result, an exogenous shock to electricity supply is likely to affect high access districts relative to low access districts. The validity of this research design relies on the assumption that absent the electricity crisis, trends in the outcome variable (employment) between low and high access (exposed) districts are parallel. In other words, the change in employment rate between the treated and control districts is uncorrelated with underlying (observable/unobservable) trends prior to the treatment.

[41] I use data from the 2000 population and housing census to compute the access rate in each district.

To test for pre-trends and the evolution of employment rates over time, I estimate an event study:

$$Y_{idt} = \sum_{\tau \neq t-\iota} \phi_{\tau} \times HighExposure_{d} \times \mathbb{I}(year = t) + \mathbf{X}'_{\mathbf{idt}}\alpha + \theta_{d} + \delta_{t} + \lambda_{YOB} + \epsilon_{ijct} \tag{5}$$

where $\mathbb{I}(year = t)$ is an indicator variable that equals 1 in year t and 0 if otherwise. All else remains as previously defined.

Results

In evaluating the effect of the power crisis on employment, I leverage two survey datasets - GLSS and Afrobarometer - spanning over the period 1998 and 2018.

Table 3 presents the DiD estimates of the effect of the power crisis on employment. For each dataset, I estimate three variant specifications to test for the robustness of the estimates to various controls. My preferred specification is column 3 (6) which is the most restrictive: including fixed effects for district, survey year, and birth-year. Individual and community characteristics such as gender, educational attainment, rural/urban status, access to road and water are also included. In addition, I control for the interaction between linear time trends and district-level characteristics such as the average homeownership and literacy rates at the baseline. These allow us to absorb trends in local economic development that may be correlated with unemployment rates across districts.

The results are stable and consistent across the two datasets. Starting with the GLSS dataset, the results in column 3 suggest that the crisis led to a 3.4 pp reduction in the probability of employment compared to a 4.7 pp reduction based on the Afrobarometer dataset (column 6). These are economically and statistically significant.

Next, I explore the trends in (un)employment rate before, during and after the crisis. These dynamics are not only important for examining parallel trends assumption, but also, the response in employment after the crisis. Results from the event study based on data from the GLSS are shown in Figure 3. First, I do not find any statistically significant differences in the trends in employment between high (treated) and low (control) access districts prior to the crisis. This provides support to the identification strategy that the estimated drop in employment during the crisis is uncorrelated with underlying differences between treated and control districts prior to the crisis. Secondly, between 2013 and 2016 (the crisis period) employment rates fell on average[42] by 7.2 pp relative to the reference period (2006).[43] Interestingly, the employment rate in 2017 (a year after the crisis ended), was about 5.6 pp lower than the reference year: an indication of a slow recovery rate in employment– and plausibly the economy– after years of exposure to the crisis.

The foregoing analysis provides additional causal evidence of the negative effects of electricity outages on employment.

4.3.2 Nigeria

Nigeria is among the leading African countries with the lowest levels of reliability in electricity supply. According to data from the World Bank Enterprise Survey, about 77.6% of Nigerian firms report experiencing outages[44] compared to the SSA average of 75.6. The number of power outages experienced by Nigerian firms in a typical month is 32.8 compared to the SSA average of 8.5. Given this, to what extent is unreliable electricity supply constraining employment in Nigeria?

I leverage unique household panel data from the Nigerian General Household Survey (GHS) to explore the effect of unreliable electricity provision on employment in the country using a fixed effect model specified as follows:

[42]the estimates for 2013 and 2016 are 6.7 pp and 7.2 pp respectively

[43]Since the crisis started briefly in the fourth quarter of 2012, I decided against using 2012 as the reference period.

[44]Based on 2014 data. See https://www.enterprisesurveys.org/en/data/exploreeconomies/2014/nigeria#infrastructure

$$Y_{ihjst} = \phi \times Outages_{j(h)st} + \mathbf{X}'_{\mathbf{ihjst}}\alpha + \theta_h + \delta_{s\times t} + \epsilon_{ihjst} \tag{6}$$

where $Outages_{j(h)st}$ is coded 1 if a household indicates frequent electricity outages[45] in the community and 0 if otherwise. In other specifications, I also explore alternate measures using the reported frequency of outages in the community. θ_h and $\delta_{s\times t}$ represent household and state $\times$year fixed effects respectively. In this setup, identification relies on within household variations in exposure to electricity outages. Thus while the distribution of outages may plausibly be non-random, within household variations in exposure to outages in their communities could be plausibly random. This assumption is arguably strong and thus the estimated effects may not be strictly causal; they nonetheless offer insights on the effects of outages conditional on household and state $\times$year fixed effects. Standard errors are clustered at the level of primary sampling unit.

Results

Table 4 presents the fixed effect estimates of the relationship between electricity outages and employment in Nigeria. In columns 1 and 4, I estimate the baseline specification without any household controls. Columns 2 and 5 include the full set of controls such as gender and educational attainment, as well as the rural/urban status of the community. In columns 3 and 6, I exclude the northeastern part of Nigeria from the analysis. Terrorist group *Boko Haram*[46] has since 2002 staged insurgency attacks in north-eastern Nigeria. This has created insecurity in the region with negative socioeconomic impact (Bertoni et al., 2019). Therefore to isolate the effects of the terrorist activities from contaminating the results, I exclude households in these areas from the estimations in columns 3 and 6.

Columns 1-3 present the results on the relationship between electricity outages and the probability of employment using a dichotomous measure of outages: defined 1 if a

[45]either daily, several times a week, several times a month or several times a year
[46]https://en.wikipedia.org/wiki/Boko_Haram

household reports experiencing outages in the community either daily, or several times a week/month/year, and 0 if otherwise. The results in column 1 (2) indicate that outages in the community are associated with a 5.7 (5.9) pp reduction in the probability of employment, and are statistically significant at 5% (10%) error level. The effect remains negative and statistically significant (5% error level), albeit slightly higher (in absolute terms) in column 3 when I exclude households from northeastern Nigeria.

In columns 4-6, I explore how the effects vary according to the intensity (frequency) of outages. The results show that outages have negative and statistically significant effects on employment in communities that experience outages either daily, several times a week, or several times a month, relative to the reference category (those who do not experience outages in their community). The effects for those who experience outages several times a year in their communities are however not statistically significant relative to the reference category.

Although causal interpretations of the fixed effects estimate require strong assumptions of exogeneity, the estimates are qualitatively and quantitatively to the DiD estimates from Ghana. Thus the results herein, once again, provide additional suggestive evidence that outages are associated with high rates of unemployment.

5 Mechanisms

This section presents evidence on the channels through which electricity outages affect employment. I explore these channels along the extensive and intensive margins. On the extensive margin, distortions in the business environment like electricity outages have the potential to discourage potential entrepreneurs to establish new enterprises due to the perceived constraints to doing business. In the intensive margin, electricity outages reduce firm performance. As a result, existing firms may either reduce their labor demand or reduce wages with potential implications on employment.

5.1 Intensive Margin

Here, I examine the effects of outages on firm performance and consequently firms' demand for labor and labor cost as potential channels underlying the outage-employment nexus. Using firm-level data from the WBES, I estimate the following IV specification:
IV first-stage:

$$Outages_{ikct} = \phi \times Lightning_{kct} + \mathbf{X}^{'}_{\mathbf{ijct}}\gamma_1 + \theta_c + \delta_{d\times t} + \epsilon_{ikct} \tag{7}$$

IV second-stage:

$$Y_{ikct} = \beta \times \widehat{Outages}_{ikct} + \mathbf{X}^{'}_{\mathbf{ikct}}\gamma_2 + \theta_c + \delta_{d\times t} + \mu_{ikct} \tag{8}$$

where Y_{ikct} is the outcome of firm i in city k, country c, and year t. $Outages_{ikct}$ is the outage intensity experienced by firm i. Two measures of outage intensity are explored here: the number (frequency) of outages a firm experiences in a typical month, and the total number of outage hours experienced by the firm in a typical month. θ_c and $\delta_{d\times t}$ represent country and industry×year fixed effects respectively. $\mathbf{X}^{'}_{\mathbf{ikct}}$ is a vector of firm, climate, and city controls including mobile phone coverage rate as a proxy for the rate of technology diffusion at the city level. $Lightning_{kct}$ is a proxy of the average lightning intensity in city k at time t. Again as highlighted in section 3.4, I use CAPE× P as a proxy for lighting intensity. Standard errors are clustered at the city level.

5.1.1 Firm Performance and Labor Demand

Table 5 presents the OLS, IV, and reduced-form estimates of the effect of outages on firm performance.[47] The results show a negative and statistically significant impact of outages on sales, sales per worker, and value-added per worker. The findings are consistent with

[47]Table A11 in the online appendix presents the first-stage results

the frequency and duration of outages. For instance, in column 2 (4), a percentage increase in the number (hours) of outages experienced by a firm reduces sales by 1.2% (0.6%). Similarly, a percent increase in the number (hours) of outages experienced by a firm reduces sales per worker by 1.3% (0.7%) (column 6 (8)). The effects on value added per worker are also negative and statistically significant: a 2.3% (2.5%) reduction in value added per worker for every percent increase in the number (frequency) of outages experienced by the firm.

Arguably, these estimates can be regarded as lower bound estimates of the total effect of outages given the fact that some firms in the dataset rely on electricity self-generation during periods of blackouts to mitigate the impact of outages. Disentangling the extent of attenuation in the impact of self-generation is, however, an empirical challenge as the decision to self-generate and the degree of self-generation are plausibly endogenous. Nonetheless, the evidence herein unambiguously highlights the challenges of African firms[48] in operating in a business environment with unreliable access to power.

Given the above negative effect of electricity outages on productivity, what are the implications on labor demand by African firms? Table 6 presents results on how electricity outages affect the number of workers hired by a firm and the associated labor cost[49]. I explore the effects of outages on the number of full-time and temporary workers employed by firms in columns 1-4 and 5-8 respectively. The effects of outages on employment of full-time (permanent) staff are negative but statistically insignificant. The effects on temporary (part-time) workers are however negative and statistically significant across all specifications: a one percent increase in the number (hours) of outages experienced by the firm is associated with a 0.6% (0.3%) reduction in the number of temporary staff employed by the firm (column 6(8)). The differences in the effects of outages on the employment of permanent and temporary staff could be associated with constraints in the labor market

[48] The term "African firms" as used in this paper, refers to firms operating in Africa, without any connotation to the nationality of its owners or country of origin.

[49] See Table A12 in the appendix for the corresponding first-stage results

such as unionization and labor laws that offer safeguards to (permanent) workers against indiscriminate layoffs. As a result, employers may resort to measures such as wage renegotiation or reduction in the number of working hours to be able to manage the negative impact of unreliable electricity provision on their activities. Substantiating these arguments requires granular data on the average working hours by the workers of firms in our sample, as well as data on the workers' wages. However, data on these measures are unavailable in the WBES. Nonetheless, I use data on total labor cost and labor cost per worker as proxies for wage and explore its relationship with outages experienced by firms.

Interestingly, the effects on total labor cost and labor cost per worker are negative and statistically significant. A percent increase in the number (hours) of outages experienced by firms is associated with a 1.1% (0.6%) reduction in labor cost (column 10 (12)). Similarly, the labor cost per worker reduces by 1.15% (column 14) and 0.64% (columns 16) respectively for every percent increase in the number and hours of outages experienced by a firm: perhaps an indication of lowering wages in response to the negative effects of outages on productivity.

I also explore how the effects of outages on firm performance vary across firm size,[50] and energy intensity. In Table A13 for instance, the results suggest that the negative effects of outages on firm performance pertain largely to small firms. The effects on medium and large firms are not statistically significant albeit negative. These results are perhaps indicative of the ability of large and medium-sized firms to invest in abatement technologies such as the use of generators or reliance on captive power generations to mitigate the unreliable grid electricity supply on their operations. Similarly, the results in Tables A14 and A15 also suggest that the outage impacts on firm performance and labor demand is largely concentrated among firms in high energy-intensive sectors. This is plausibly due to the critical role of electricity in the daily operations of firms in such sectors.

[50]Definition of firms are as follows: small firms (¡20 employees), medium (20-99 employees), and large (100 and above employees)

Overall, the results in Table 5 provide suggestive evidence that outages negatively affect the performance of firms. Firms respond to this negative shock by reducing demand for temporary workers, and reducing wages so as to avoid (massive) lay-offs of permanent full-time staff (see Table 6). Available evidence from the relatively scant literature on the effects of electricity outages on firm productivity and labor demand lends support to the findings of this paper (Allcott et al., 2016; Hardy and McCasland, 2019; Abeberese et al., 2021). Allcott et al. (2016) for instance provide evidence of significant revenue and productivity losses resulting from electricity outages in India. Also using data on small garment firms in Ghana, Hardy and McCasland (2019) show that the effect of electricity outages on firm revenue and profitability is non-trivial. Hardy and McCasland (2019) further show that firms respond to these shortages by reducing production hours without any allocation to non-outage days, and more importantly substituting high-wage employees for low-wage employees.

5.2 Extensive Margin

In this section, I provide evidence on how unreliable electricity provision constrains job creation on the extensive margin by showing the effects on: (i) (net) entry of firms using data from Ethiopia, and (ii) entry of foreign firms via FDI exploiting the "Dumsor" crisis in Ghana as a natural experiment.

5.2.1 Firm Entry

The entry of new firms is an important channel for job creation as it leads to the expansion of the productive sectors and employment opportunities. Examining the effects of unreliable power provision on entry (and exit) of firms is however a challenge mainly due to the lack of administrative data on firms. In many African countries, firm census are scant, with the exception of Ethiopia and South Africa that conduct yearly censuses of firms. An additional challenge is that even where firm census data are available, there is a dearth of information on the quality of electricity supply, thus constraining empirical assessment of the role of electricity shortages on (net) entry of firms.

In this section, I use firm census data from Ethiopia to show the relationship between exposure to outages and the density of (manufacturing) firms across locations in the country and also show how outages influence the operation (shutdown) of (manufacturing) firms in the country. Specifically, I estimate the following fixed effect specification

$$Y_{it} = \phi \times UnreliableSupply_{it} + \mathbf{X_{it}'}\alpha + \theta_i + \delta_t + \epsilon_{it} \tag{9}$$

where Y_{it} is a placeholder for firm outcomes in location (district or city) i at time i, $UnreliableSupply_{it}$ is a measure of unreliable electricity provision at location i in time i, $\mathbf{X_{it}'}$ is a vector of controls, while θ_i and δ_t represent location and time fixed effects respectively. The analysis is conducted at district and firm levels. In the district-level analysis, two main outcomes are explored: the number of firms in a district (Woreda) in a given year, and firm density (i.e. the number of firms per 1000 people). These outcomes represent the (net) entry of firms across various districts in Ethiopia in a given period. Thus, using these outcomes, I explore the potential effect of unreliable electricity provision on the intensity of (manufacturing) firms across locations. A priori, unreliable electricity provision in a given locality is expected to influence the exit (and entry) of firms thereby resulting in low firm density. In the firm-level analysis, the main outcome is the number of months in a year that the firm operates. Again, firms exposed to frequent outages often shut down during outage periods relative to firms with reliable supply.

Further, in the district-level analysis, $UnreliableSupply_{it}$ is measured by the share of firms in a district citing electricity outages as a major constraint to their activities. In the firm level analysis,[51] $UnreliableSupply_{it}$, is a dummy variable equal to 1 if a firm reports electricity outages as a major constraint to its operation and 0 if otherwise. Arguably, exposure to outages is non-random across space and time, hence estimates from equation (9) cannot be ascribed causal interpretations. In other words, $\hat{\phi}$ shows the association between exposure to outages and net entry of firms. Finally, I also explore how the association between outages and (net) firm entry varies between "high energy-intensive" and "low energy-intensive" industries. Standard errors are clustered at the location level.

Results

Table 7 presents the results on the association between exposure to outages and firm density, and extent of operation. Starting with the district-level analysis, column (1-2) shows the relationship between outage intensity and the number of firms operating in a district. According to the results, a 1 pp increase in the share of firms experiencing outages is associated with a 1.7% reduction in the number of firms operating in the district.[52] In other words, moving from a district with (fully) reliable supply of electricity to one with an unreliable supply reduces the number of firms operating in the district by almost one-fifth. Obviously, proximity to markets is a key determinant of firm location (concentration). As a result, more (manufacturing) firms are likely to be located in densely populated areas like large cities relative to small towns.[53] To account for this, in column 3-4, I use firm density (i.e., number of firms per 1000 people) as the outcome and explore the association with intensity of outages experienced by firms. Again the results show a negative association. These results suggest that unreliable electricity provision has negative impacts on the entry (and exit) of firms across locations. To further understand the effects of

[51] Despite being an annual survey, information on unique firm identifiers in the LMMIS are scant (Hjort and Poulsen, 2019; Abebe et al., 2018). This limits the ability to exploit the panel structure of firms. Thus, in this analysis, I treat the data as a repeated cross-section rather than estimating within-firm variations.

[52] $exp^{\hat{\beta}} - 1 = exp^{-.0191} - 1 \approx 0.17$

[53] Access to infrastructure like roads, electricity, water, and internet are also more readily available in densely populated areas cities relative to small towns

unreliable electricity provision firm entry, columns 5-6 and 6-7 present the results on the association between outage intensity and the number of (manufacturing) firms operating in ″high energy-intensive″ and ″low energy-intensive″ sectors respectively. Interestingly, the results show a negative and statistically significant effect of outages on the number of firms operating in ″high energy-intensive″ sectors. Meanwhile, the effect on the number of firms operating in ″low energy-intensive″ sectors is also negative, albeit statistically insignificant.

It is important to emphasize that the number (density) of firms operating each year is a net measure of firm entry and exit. While, outages are likely to affect both entry and exit, disentangling the effects is difficult due to data constraints. To provide insights into this, I conduct a firm-level analysis to explore the effect of firms' exposure to outages and the duration of their operations in a given year. Given the importance of access to electricity in the production process, firms exposed to outages are more likely to shut down production during outage periods. Continuous shutdown of operations may contribute to their exit from the market. In panel B of Table 7, I show that firms with reliable supply operate for longer periods in a year than their counterparts with unreliable supply. Across the various specifications, the results suggest that conditional on the location, industry, ownership and time fixed effects, the average number of operating months is about one month lower for firms with unreliable electricity supply relative to their counterparts with reliable electricity supply. Interestingly, the effect holds for firms operating in both ″high energy-intensive″ and ″low energy-intensive″ sectors: perhaps an indication of the direct and indirect effects of outages on firm operations. While these estimates measure association, they provide suggestive evidence of the effects of outages on the entry and exit of firms in Ethiopia.

5.2.2 FDI

Next, I explore the effects of unreliable electricity provision on the entry of foreign firms via FDI. In many developing and emerging countries, FDI is a potent source of firm entry as foreign investors enter these markets to harness the natural and human capital, and establish businesses in these economies. These new firms ultimately generate jobs for local people (Toews and Vézina, 2021). For instance, Toews and Vézina (2021), using data on Mozambique estimates to estimate the FDI-local job multiplier finds that each new FDI-job creates an additional 4.4 jobs of which 2.1 are formal jobs. In other words, aside the direct jobs creation associated with FDI's (eg., employment of factory workers), FDI's generates indirect jobs resulting from sectoral linkages.[54] Thus, FDI is a key channel for job creation in many developing countries, hence, factors that constrain FDI flows could have negative implications on employment.

The economic effects (including employment) associated with FDIs have made the attraction of FDI a key development strategy of emerging economies. However, the quality of infrastructure provision such as electricity plays an important role in the flow (direction) of FDI to developing economies. Cost of doing business is an important driver of FDI flows as it influence the returns on investment to investors. Meanwhile, the reliability of electricity provision is a significant determinant of the cost of doing business. For instance, during blackouts some firms rely on in-house electricity generation which are expensive relative to grid supply, while others curtail production. These options invariably have negative effects on firms' profitability. In addition, persistent reliability issues in the electricity sector can generate adverse macroeconomic shocks in the economy thereby affecting investor confidence.

In section, I ask: to what extent does unreliable provision of electricity affect FDI flows? To address this question, I exploit the "Dumsor" power crisis in Ghana as a natural exper-

[54] For instance, FDI into manufacturing, may generate increased demand for intermediate inputs within the value chain, which ultimately creates jobs.

iment and show how FDI flows to the country were affected by the crisis.[55] Specifically, I focus on greenfield FDI in the non-energy-and-construction sectors (hereafter referred to as FDI [excl. energy & construction] projects) as: (i) the crisis could have induced significant investment into the energy sector as part of efforts to resolve the crisis. Hence,FDI to the sector may rise in response to the crisis; and (ii) construction related FDIs, such as investment in real estate, are unlikely to respond to energy crisis as these sectors are relatively low energy intensive.

To causally estimate the effect of the crisis on FDI in Ghana, I use the synthetic control approach (SCM) (Abadie and Gardeazabal, 2003; Abadie et al., 2010, 2011, 2015; Peri and Yasenov, 2019; Andersson, 2019). The basic idea behind the SCM is to construct a counterfactual, otherwise referred to as "synthetic control" using a weighted combination of the outcome variable in the control (donor) units that matches the outcome variable of the treated unit in the pre-treatment period. The weights are constructed via a data-driven algorithm by minimizing the differences in the outcome variable as well as key predictors of the outcome variable between the treated and control units. These weights are then used to construct a weighted combination of the outcome variable in the post-treatment period, which serves as a valid counterfactual for the treated unit during the post-treatment period. Therefore, the difference in the observed outcome between the treated unit and the synthetic control (counterfactual) measures the effect of the treatment.[56] A unique feature of the SCM is that, unlike the DiD, the so-called "parallel trends" assumption is not required for identification.

The analysis is undertaken using a panel data on the greenfield FDI projects (excl. energy and construction sectors) in 23 emerging markets in Africa, Latin American and

[55]There are at least two factors that motivate the choice of the Ghanaian crisis as a unique experiment: First, the crisis was a large scale shock to the economy as almost every economic sector and geographic administration in the country was affected. Second, the prolonged nature of the crisis (2013-2016) provides a unique opportunity to assess the effects of a relatively "long-term" shock as opposed to an instantaneous shock.

[56]The SCM is somewhat similar to the DiD method, except that unlike the latter, the former does not impose equal weights on the control units

Caribbean, and Asia[57] between 2007 and 2017. The choice of these countries was mainly informed by data availability and also countries that provide the relevant weights in constructing the synthetic control.[58] The dataset among others provides information on the number unique of FDI projects in each country, sector, and year. I focus mainly on count of investments rather than the monetary value of the investments as these FDI projects are heterogeneous across industry, country and year. Also the number of FDI projects into a country signals the response of various investors to the business environment in the destination country. The main predictors used include lags of the number of FDI [excl. energy & construction] projects, the log of GDP (2007-2008) and total FDI (all sectors) (2009-2012), GDP growth rate (2012) and population.

Results: Ghana vs Synthetic Ghana

The intuition behind the SCM is that if "Synthetic Ghana" is able to track the flow of FDI to Ghana in the pre-crisis era, then it provides a credible counterfactual of the flow of FDI to Ghana in the absence of the power crisis between 2013 and 2016. This section presents the main findings of the SCM. Tables A9 in the online appendix present the summary statistics of the predictors between Ghana vs. "Synthetic Ghana", as well as the sample average during the pre-treatment period. Also, Table A10 in the online appendix shows the distribution of the weights used in constructing the "synthetic control" across the control (donor) countries. Kenya, Zambia and Zimbabwe account for the largest share with weights of 0.57, 0.24, and 0.13 respectively.

In terms of the main results, Figure 4 plots the number of FDI [excl. energy & construction] projects in Ghana and Synthetic Ghana before, during and after the crisis. As shown

[57]Cambodia, Ghana, Guatemala, Honduras, India, Jamaica, Kenya, Morocco, Mexico, Myanmar, Mauritius, Namibia, Nicaragua, Pakistan, Philippines, Senegal, South Africa, Uganda, Uruguay, Uzbekistan, Vietnam, Zambia, Zimbabwe

[58]More so non-African countries were included in the control to limit the potential violation of the stable unit treatment value assumption (SUVTA) which is likely to be violated if, for instance, the power crisis in Ghana shifted FDI into neighboring countries or other African countries with similar business environment with the pre-crisis Ghana.

in the figure, prior to the crisis, FDI in synthetic Ghana tracks FDI in Ghana very closely. The average (absolute) difference in the number of FDI projects between Ghana and its synthetic counterpart in the pre-crisis period is just -0.34. However, as seen in the figure, the path-plot of the two units begins to diverge during the crisis period (2013-2016) and even persists in the post-crisis period (2017). Interestingly, the results show a consistent fall in the number of FDI [excl. energy & construction] projects in Ghana between 2013 and 2016, rising marginally in 2017.

The gap (difference) in FDI between Ghana and its counterfactual in the pre/post period are shown in Figure 5. In 2014 (a year into the crisis), the gap between the number of non-energy FDI projects in Ghana and its synthetic counterpart is marginal (8%). However, in 2015 (two years into the crisis), we observe a significant dip in FDI flows to the non-energy sectors in Ghana relative to its synthetic counterpart. For instance, in 2015 a total of 28 FDI projects in the non-energy-and-construction sectors were implemented in Ghana compared to an estimated counterfactual of 49.3. This represents 43% reduction in the number of FDI projects in the non-energy-and-construction sectors for the year. There was a slight improvement in 2016 with the gap reducing to 12%. The negative effects of the crisis persisted in 2017 – a year after the crisis was officially declared over, with a 27% reduction in the number of non-energy FDI project inflows. Overall, how did the power crisis affect FDI inflows? The estimates from the synthetic control analysis indicate that between 2013 and 2016, the power crisis on average resulted in a reduction in the number of non-energy sector FDI by 12.3% per annum.

To assess the statistical significance of the gap between the observed FDI in Ghana and its synthetic counterpart, I follow the approach of Abadie et al. (2010, 2015) in constructing an "exact p-value". The approach involves estimating iteratively the SCM for each country in the donor pool (i.e., the control countries) and obtaining the distribution of the respective placebo effects. Based on these placebo effects, the ratio of the root mean square prediction error (RMSPE) in the post-treatment period to the RMSPE for the pre-treatment is computed and ranked across countries. The p-value is computed by dividing the rank of the treatment country (unit) by the total number of countries in the pool (Cunningham, 2021). Figure A5 in the appendix shows the distribution of the post-pre RSMPE ratio for all countries in the pool. Based on the results in the figure, Ghana is ranked second out of the 23 country units, which implies an "exact p-value" of 0.086.[59] In other words, the SCM results are statistically significant at 10% error level.

These results provide suggestive evidence that the quality of electricity supply is a major determinant of FDI flows. To the extent that unreliable provision of electricity supply reduces FDI inflows, the findings suggest that a reduction in firm entry via falling (greenfield) FDIs is a mechanism through which electricity shortages affect employment since FDI is an important avenue for job creation in many developing countries (Toews and Vézina, 2021). It is important to acknowledge that the estimated effect of outages on FDI only reflects the impact on the entry of foreign firms.

Robustness

To test the robustness of the SCM results, I conduct two placebo ("in-time" and "in-space") tests. Starting with the placebo "in-time" test, I explore the possibility of finding a similar gap in the FDI trends between Ghana and its synthetic control assuming a placebo treatment period. Specifically, I focus on the period 2007-2013 and assign 2011 as the treatment year. Finding a large placebo gap suggests that the results in Figures 4 and 5 are unlikely to be the causal impact of the power crisis on FDI. That is the effect could arise out of chance and not related to the impact of the power crisis. As shown in Figure A6, I find no evidence of significant divergence between Ghana and its synthetic control using the placement treatment period.

In the case of the "in-space" placebo test, I iteratively assign treatment status to countries in the control (donor) pool while using the remaining countries (including Ghana)

[59] i.e., $1/23 = 0.086$

to construct the respective counterfactual via the synthetic control method. The estimated gap in observed FDI and the counterfactual for the respective countries are compared to determine if the gap for Ghana is unusually large or comparable to the results for the other countries. Figure A7 (Panel A) shows the results of the placebo "in-space" test for all countries in the dataset. However, as shown in the plot, the SCM is unable to find a convex combination of donor units that replicates the gap plot for Ghana in the pre-treatment period. As a result, there is a large variance in the gap between Ghana and several countries in the pre-treatment period. Therefore following Abadie et al. (2010), in Panel B of A7, I drop countries where the pretreatment MSPE is considerably large (>20) than Ghana's MSPE. Encouragingly aside from having a pre-treatment gap similar to Ghana, the results in Panel B shows that Ghana has the largest reduction in FDI in the post-treatment period. These placebo tests, together with the estimated p-value provide suggestive evidence that the SCM results in Figures 4 and 5 are statistically different from zero.

In addition to the above, I also conduct additional robustness checks by performing the SCM analysis on FDI in the construction and energy sectors. Recall that up to this point the SCM analysis relies on data on FDI in sectors excluding energy and construction. In Figures A8 for instance, the path plot shows a slight increase in FDI into Ghana's energy sector in Ghana relative counterfactual levels in 2014 and 2015, plausibly indicative of the Government's response in attracting FDI into the sector to address the power deficit in the country. FDI in the sector, however, fell significantly relative to the counterfactual 2016 when the crisis ended. In the case of the construction sector, as shown in Figure A9, I do not find any consistent evidence of the effect of the power crisis on FDI in the sector. Between 2013 and 2014, construction FDI in Ghana increased relative to the counterfactual, however, we observe a complete reversal in 2015 and 2016. Thus, the net effect of the gap between FDI in Ghana and its counterfactual (synthetic Ghana) during the period of the power crisis is approximately zero.

Overall, in line with the results in Section 5.2.1, the results herein provide additional suggestive evidence of the negative impact of unreliable electricity provision on the entry of new firms in an economy.

6 Discussion and Conclusion

Many African countries are confronted with rising unemployment. At the same time, many economies in the region grapple with unreliable provision of electricity to households and industry, with potential implications on economic performance. The extent to which unreliable provision of electricity contributes to the growing unemployment in the region is a question central to development policy in the region.

This paper presents evidence of how electricity shortages constrain job creation in Africa. To this end, I assemble an array of household and firm data across several SSA countries, along with unique data on greenfield FDI projects to: (i) estimate the extent to which outages affect employment, and (ii) the channels through which these impacts arise. Findings from the paper indicate that electricity outages are a major contributory factor to the growing unemployment in Africa. Skilled jobs and employment in non-agricultural sectors are the most affected. Specifically, from the cross-country analysis, the results from an IV regression estimation suggest that outages are associated with a 13.5 pp decrease in the probability of employment. Estimates from country-case studies in Ghana and Nigeria suggest that outages are associated with a 4.7 pp and 5.7 pp reduction in the probability of employment respectively. Factors such as cross-country heterogeneity and differences in the measure of employment and outages across the various datasets could account for the differences in the point estimates. Nonetheless, the estimates fall in a similar ballpark, suggesting that outages reduce employment by between 4.7 and 13.5 pp.

Further, the paper provides suggestive evidence of two plausible mechanisms. First outages constrain firm entry via: a reduction in firm density, and foreign direct investment in non-energy-and-construction sectors due to the effect of outages on the cost of doing business thereby serving as a disincentive to entrepreneurs and investors. Secondly, outages have a significant negative effect on the performance of incumbent firms thereby constraining the expansion of the productive sectors of the economy.

The findings of this paper have important implications for policy. The results provide suggestive evidence that resolving the challenges in the electricity sector is an important channel towards expanding the industrial sector as it will increase job creation. Again, access to reliable electricity is crucial for improving the productivity of incumbent firms and attracting new (domestic and foreign) firms including FDI. These will contribute to increasing the number of employment opportunities in the region and ultimately reduce the high rate of unemployment in many African economies.

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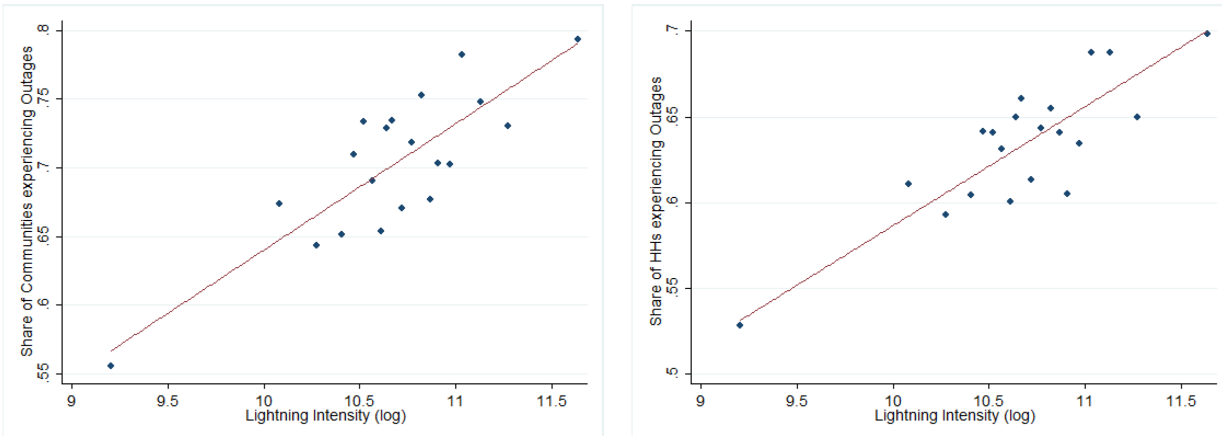
Figures

Figure 1: Relationship between Outages and Lightning Intensity



The (binned) scatter plots above shows the relationship between outages and lightning intensity. The left panel shows the correlation between the share of communities experiencing outages and lightning intensity; while the right panel shows the correlation between the share of households in a community experiencing outages and lightning intensity.

Figure 2: Electricity Rationing Schedule during the Power Crisis in Ghana (2015)

LOAD-SHEDDING GUIDE

The Electricity Company of Ghana wishes to inform its cherished customers that due to generation shortfall it has become necessary to publish this load shedding guide.

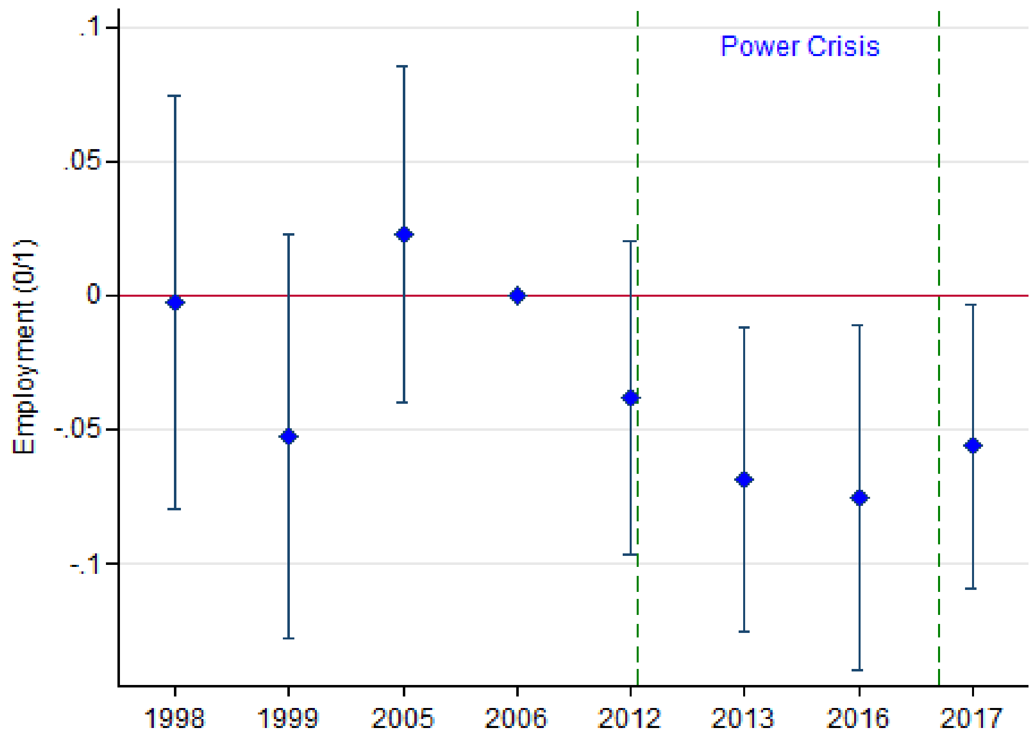
All Communities in the bracket are on loadshedding, but all or some may not go off depending on the quantum of power to be shed.

	FRIDAY 06/02/2015	SATURDAY 07/02/2015	SUNDAY 08/02/2015	MONDAY 09/02/2015	TUESDAY 10/02/2015	WEDNESDAY 11/01/2015	THURSDAY 12/02/2015
DAY 6AM TO 7PM	B; (A)	C; (B)	A; (C)	B; (A)	C; (B)	A; (C)	B; (A)
NIGHT 6PM TO 6AM	A; (C)	B; (A)	C; (B)	A; (C)	B; (A)	C; (B)	A; (C)
	FRIDAY 13/02/2015	SATURDAY 14/02/2015	SUNDAY 15/02/2015	MONDAY 16/02/2015	TUESDAY 17/02/2015	WEDNESDAY 18/01/2015	THURSDAY 19/02/2015
DAY 6AM TO 7PM	C; (B)	A; (C)	B; (A)	C; (B)	A; (C)	B; (A)	C; (B)
NIGHT 6PM TO 6AM	B; (A)	C; (B)	A; (C)	B; (A)	C; (B)	A; (C)	B; (A)
	FRIDAY 20/02/2015	SATURDAY 21/02/2015	SUNDAY 22/02/2015	MONDAY 23/02/2015	TUESDAY 24/02/2015	WEDNESDAY 25/01/2015	THURSDAY 26/02/2015
DAY 6AM TO 7PM	A; (C)	B; (A)	C; (B)	A; (C)	B; (A)	C; (B)	A; (C)
NIGHT 6PM TO 6AM	C; (B)	A; (C)	B; (A)	C; (B)	A; (C)	B; (A)	C; (B)
	FRIDAY 27/02/2015	SATURDAY 28/02/2015	SUNDAY 01/03/2015	MONDAY 02/03/2015	TUESDAY 03/03/2015	WEDNESDAY 04/03/2015	THURSDAY 05/03/2015
DAY 6AM TO 7PM	B; (A)	C; (B)	A; (C)	B; (A)	C; (B)	A; (C)	B; (A)
NIGHT 6PM TO 6AM	A; (C)	B; (A)	C; (B)	A; (C)	B; (A)	C; (B)	A; (C)
	FRIDAY 06/03/2015						
DAY 6AM TO 7PM	C; (B)						
NIGHT 6PM TO 6AM	B; (A)						

Below is the list of Affected Areas. Customers should please identify their areas and consult the time table. Customers can also access the load shedding guide at our website: www.ecggh.com. For further enquiries, please call our Contact Centre on 0302-611611.

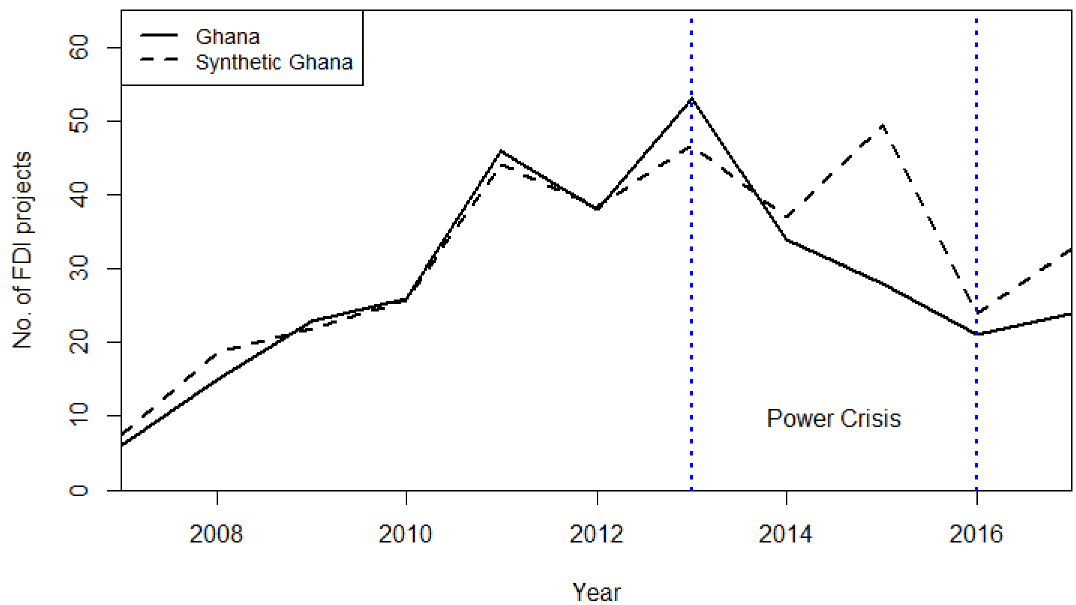
This figure shows an example of the power rationing schedule by the Electricity Company of Ghana (ECG) during the "dumsor" power crisis in 2015. Source: Daily Graphic (2015)

Figure 3: Event Study- The "Dumsor" Power Crises and Unemployment in Ghana



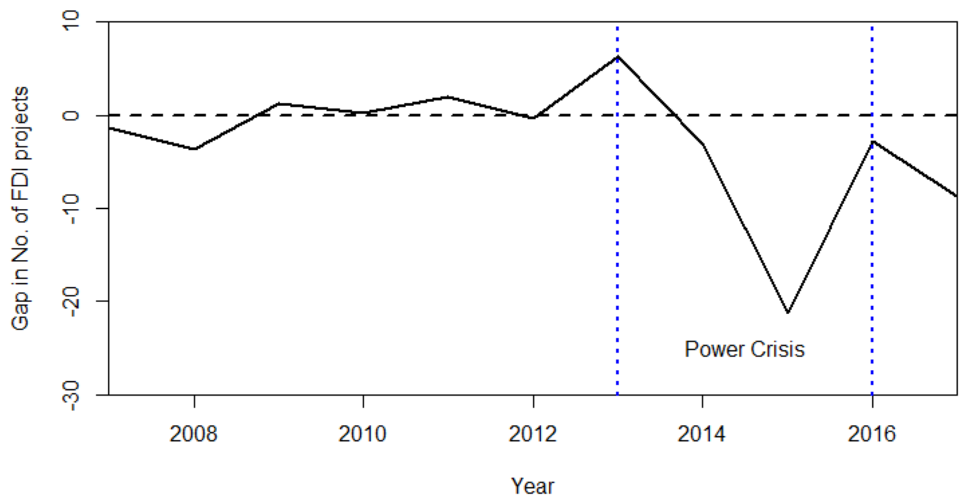
This figure shows the coefficients and 95% confidence intervals from an event study regression that estimate the interactions between year and high exposure indicators, where the outcome variable is an indicator for the employment status of a person, and year 2006 is the omitted category. High Exposure is an indicator variable equal to 1 if the district's electricity access rate in the year 2000 is above the median access rate in the country and 0 if otherwise. The regression controls for gender, education, rural-urban status, access to roads, access to water, and the following fixed effects: district, year and birth-year.

Figure 4: Path Plot of Number of FDI Projects during 2007-2017: Ghana vs Synthetic Ghana



This plot shows the trend in the number of ”non-energy” sector FDI projects in Ghana vs a Synthetic Ghana before and during the power crisis

Figure 5: Gap in the Number of FDI Projects between Ghana and Synthetic Ghana



This plot shows the gap in the number of "non-energy" sector FDI projects in Ghana and a Synthetic Ghana before and during the power crisis

Tables

Table 1: First Stage Regression: Electricity Outages and Lightning Intensity

	Outages in Community (0/1)		Outages in Community (% HHs)	
	(1)	(2)	(3)	(4)
Lightning intensity (log)	0.119***	0.119***	0.087***	0.088***
	(0.012)	(0.012)	(0.008)	(0.008)
Controls	Yes	Yes	Yes	Yes
Country FE	Yes	Yes	Yes	Yes
Survey Year FE	Yes	No	Yes	No
Survey Round FE	No	Yes	No	Yes
Kleibergen-Paap F statistic	92.383	93.529	121.927	124.648
Observations	24999	24999	24999	24999

Notes: In columns 1-2, the dependent variable is a dummy set equal to 1 if more than 50% of connected households in the PSU do not have access to reliable electricity, and 0 if otherwise. In column 3-4, the dependent variable is the share of connected households in the PSU do not have access to reliable electricity. Controls included are gender, age, age squared, educational attainment, mobile phone coverage, and the logs of total precipitation and mean annual temperature. Standard errors clustered at the PSU level included in parenthesis.
* Significant at 10 percent level
** Significant at 5 percent level
*** Significant at 1 percent level

Table 2: Electricity Shortages and Employment

	All						Skilled Workers		Unskilled Workers	
	Employed (0/1)		Employed in Non-Agric (0/1)		Employed in Agric (0/1)		Employed (0/1)			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
	OLS									
Outages in Community (0/1)	-0.021**	-0.020**	-0.028***	-0.027***	0.007	0.007	-0.013	-0.012	-0.061***	-0.060***
	(0.010)	(0.010)	(0.010)	(0.010)	(0.005)	(0.005)	(0.012)	(0.012)	(0.021)	(0.021)
	IV									
Outages in Community (0/1)	-0.137**	-0.135**	-0.137**	-0.135**	0.000	0.000	-0.192***	-0.191***	-0.024	-0.020
	(0.062)	(0.062)	(0.063)	(0.063)	(0.027)	(0.027)	(0.070)	(0.070)	(0.133)	(0.133)
	Reduced Form									
Lightning Intensity (log)	-0.016**	-0.016**	-0.016**	-0.016**	0.000	0.000	-0.024***	-0.024***	-0.003	-0.002
	(0.007)	(0.007)	(0.007)	(0.008)	(0.003)	(0.003)	(0.008)	(0.008)	(0.016)	(0.016)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Country FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Survey Year FE	Yes	No	Yes	No	Yes	No	Yes	No	Yes	No
Survey Round FE	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes
Mean dep. Var	0.583	0.583	0.522	0.522	0.061	0.061	0.658	0.658	0.486	0.486
Kleibergen-Paap F statistic	92.383	93.529	92.383	93.529	92.383	93.529	95.539	96.389	43.303	43.749
Observations	24999	24999	24999	24999	24999	24999	16924	16924	4143	4143

Notes: Dependent variable(s) is a measure of employment status of the individual. It is a dummy equal to 1 if the individual is employed and 0 if otherwise. Controls included are gender, age (log) and educational attainment, mobile phone coverage, and the logs of total precipitation and mean annual temperature. Standard errors clustered at the PSU level included in parenthesis.
* Significant at 10 percent level
** Significant at 5 percent level
*** Significant at 1 percent level

Table 3: Effect of Power Crises on Employment in Ghana

	GLSS			Afrobarometer		
	(1)	(2)	(3)	(4)	(5)	(6)
High Exposure × Power Crisis	-0.0455***	-0.0368**	-0.0341**	-0.0515*	-0.0499*	-0.0472*
	(0.0124)	(0.0175)	(0.0171)	(0.0268)	(0.0267)	(0.0283)
District FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
YOB FE	Yes	Yes	Yes	Yes	Yes	Yes
Indiv. & Comm. Controls	No	Yes	Yes	No	Yes	Yes
District Ctrls × Trend	No	No	Yes	No	No	Yes
Mean dep. var	0.7399	0.7474	0.7474	0.7271	0.7274	0.7274
R-squared	0.3632	0.3812	0.3822	0.1371	0.1434	0.1435
Survey Rounds	4	4	4	6	6	6
Observations	102487	41464	41464	8663	8644	8644

Notes: Dependent variable is a dummy variable equal to 1 if the individual is employed and 0 if otherwise. Indiv. & Comm. Controls represent individual and community attributes such as gender, highest educational attainment of the respondent, rural/urban status, access to road and water in the community. District Ctrls × Trend include the baseline homeownership and literacy rates in the district interacted with a time trend. Standard errors are clustered at the district level. OLS estimations.
* Significant at 10 percent level ** Significant at 5 percent level *** Significant at 1 percent level

Table 4: Panel Fixed Effect Regression: Electricity outages and Employment in Nigeria

	Employed (1/0)					
	(1)	(2)	(3)	(4)	(5)	(6)
Outages in Community (0/1)	-0.0565**	-0.0585*	-0.0631**			
	(0.0277)	(0.0306)	(0.0290)			
Frequency of outages						
Daily				-0.0519*	-0.0540*	-0.0605**
				(0.0290)	(0.0317)	(0.0298)
Several times a week				-0.0569**	-0.0604*	-0.0627**
				(0.0285)	(0.0322)	(0.0310)
Several times a month				-0.0826***	-0.0841***	-0.0831**
				(0.0303)	(0.0321)	(0.0325)
Several times a year				-0.0550	-0.0596	-0.0524
				(0.0385)	(0.0433)	(0.0439)
Indiv Controls	No	Yes	Yes	No	Yes	Yes
HH FE	Yes	Yes	Yes	Yes	Yes	Yes
State× Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Excluding North East	No	No	Yes	No	No	Yes
Mean dep. var	0.7850	0.7883	0.7937	0.7850	0.7883	0.7937
R-squared	0.3081	0.3450	0.3358	0.3083	0.3452	0.3360
Survey Rounds	3	3	3	3	3	3
Observations	16134	12888	11907	16134	12888	11907

Notes: Dependent variable is a dummy equal to 1 if the individual is employed and 0 if otherwise. Individual Controls included gender, educational attainment and rural/urban status. Standard errors clustered at the PSU level included in parenthesis.
* Significant at 10 percent level ** Significant at 5 percent level *** Significant at 1 percent level

Table 5: IV Regression: Electricity outages and Firm Performance

	Dependent Var:											
	Log Sales				Log Sales/Worker				Log Value Added/Worker			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
	OLS											
Outages (log)	-0.1441*	-0.1427*			-0.1137	-0.1137			0.0388	0.0388		
	(0.0739)	(0.0754)			(0.0753)	(0.0747)			(0.0903)	(0.0903)		
Outage Hours (log)			-0.1625***	-0.1554***			-0.1242***	-0.1178***			-0.0266	-0.0266
			(0.0432)	(0.0426)			(0.0318)	(0.0313)			(0.0442)	(0.0442)
	IV											
Outages (log)	-1.1536*	-1.1672**			-1.2862**	-1.2700**			-2.3427**	-2.3427**		
	(0.5798)	(0.5575)			(0.6084)	(0.5870)			(0.8865)	(0.8865)		
Outage Hours (log)			-0.5989*	-0.6132*			-0.6850*	-0.6828*			-2.4713*	-2.4713*
			(0.3271)	(0.3212)			(0.3535)	(0.3472)			(1.4199)	(1.4199)
	Reduced Form											
Lightning intensity (log)	-0.7650**	-0.7856**	-0.7228**	-0.7446**	-0.8856**	-0.8873**	-0.8554**	-0.8548**	-1.1596***	-1.1596***	-1.1708***	-1.1708***
	(0.3533)	(0.3441)	(0.3532)	(0.3429)	(0.3532)	(0.3422)	(0.3592)	(0.3451)	(0.3577)	(0.3577)	(0.3476)	(0.3476)
Firm Ctrls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Climate Ctrls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes	No
Industry$\times$Year FE	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes
Country FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes	No
Kleibergen-Paap F statistic	31.7013	30.5283	19.6054	19.9313	35.6018	34.4263	21.7683	21.6960	20.8382	20.8382	4.7931	4.7931
Observations	3789	3789	3617	3617	3743	3743	3572	3572	1616	1616	1556	1556

Notes: Firm Controls include: age of the firm, whether the firm is foreign or domestic, and the mobile phone coverage rate in the city of the firm. Climate controls include the log of total precipitation and mean annual temperature. Standard errors clustered at the city level included in parenthesis.
* Significant at 10 percent level ** Significant at 5 percent level *** Significant at 1 percent level

Table 6: IV Regression: Electricity outages and Labor Demand

	First Stage Dep. Var:															
	Log # of Full Time Workers				Log # of Temp. Workers				Log Labor Cost				Log Labor Cost per Worker			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)
	OLS															
Outages (log)	-0.0197	-0.0186			0.0409	0.0411			-0.2057**	-0.2061**			-0.1905***	-0.1919***		
	(0.0356)	(0.0346)			(0.0338)	(0.0350)			(0.0840)	(0.0819)			(0.0601)	(0.0589)		
Outage Hours (log)			-0.0227	-0.0232			0.0021	0.0031			-0.2095***	-0.2057***			-0.1784***	-0.1745***
			(0.0244)	(0.0239)			(0.0238)	(0.0261)			(0.0580)	(0.0542)			(0.0444)	(0.0417)
	IV															
Outages (log)	-0.1654	-0.1780			-0.6165***	-0.5809***			-1.1320*	-1.1335*			-1.1494*	-1.1499*		
	(0.2358)	(0.2459)			(0.2056)	(0.2142)			(0.6505)	(0.6084)			(0.6777)	(0.6348)		
Outage Hours (log)			-0.0818	-0.0909			-0.3359***	-0.3195***			-0.6256	-0.6342*			-0.6348	-0.6406*
			(0.1228)	(0.1301)			(0.1044)	(0.1086)			(0.3812)	(0.3614)			(0.4001)	(0.3774)
	Reduced Form															
Lightning intensity (log)	-0.1000	-0.1092	-0.0942	-0.1052	-0.3726***	-0.3564**	-0.3868***	-0.3698**	-0.7288*	-0.7439*	-0.7195*	-0.7359*	-0.7357*	-0.7503**	-0.7292*	-0.7423**
	(0.1447)	(0.1549)	(0.1442)	(0.1552)	(0.1228)	(0.1377)	(0.1234)	(0.1379)	(0.3914)	(0.3799)	(0.3908)	(0.3759)	(0.3709)	(0.3509)	(0.3708)	(0.3457)
Firm Ctrls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Climate Ctrls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes	No
Industry×Year FE	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes
Country FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes	No
Kleibergen-Paap F statistic	25.6449	24.1860	22.8923	22.6933	25.6449	24.1860	22.8923	22.6933	31.3946	29.6312	16.9568	17.3329	30.7593	29.0558	16.9526	17.3191
Observations	4281	4281	4076	4076	4281	4281	4076	4076	3809	3809	3650	3650	3803	3803	3644	3644

Notes: Firm Controls include: age of the firm, whether the firm is foreign or domestic, and the mobile phone coverage in the city of the firm. Climate controls include the log of total precipitation and mean annual temperature. Standard errors clustered at the city level included in parenthesis.
* Significant at 10 percent level ** Significant at 5 percent level *** Significant at 1 percent level

Table 7: Electricity Shortages and and Net Firm Entry

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	A: District Level Analysis							
	All Firms				High Energy Intensive		Low Energy Intensive	
	log (# of firms)		# firms per 1000 people		log (# of firms)			
Share of firms with unreliable supply	-0.192**	-0.191**	-0.013*	-0.013*	-0.133**	-0.137**	-0.091	-0.086
	(0.08)	(0.079)	(0.008)	(0.007)	(0.061)	(0.061)	(0.060)	(0.058)
Controls	No	Yes	No	Yes	No	Yes	No	Yes
District FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R2	0.857	0.858	0.955	0.964	939	939	939	939
MP	1.486	1.486	0.106	0.106	0.9687	0.9687	1.4456	1.4456
Obs	939	939	939	939	939	939	939	939
	B: Firm Level Analysis							
	All Firms				High Energy Intensive		Low Energy Intensive	
	# of months operating							
Firm experiencing unreliable supply (0/1)	-0.905***	-1.008***	-0.911***	-0.987***	-1.020***	-1.036***	-0.856***	-0.845***
	(0.066)	(0.063)	(0.067)	(0.065)	(0.105)	(0.107)	(0.065)	(0.065)
Controls	No	Yes	No	Yes	No	No	No	No
District FE	Yes	Yes	No	No	Yes	No	Yes	No
Year FE	Yes	No	Yes	Yes	Yes	Yes	Yes	Yes
City/Town FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Ownership type FE	Yes	No	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	No	Yes	No	No	No	No	No	No
IndustryXYear FE	No	No	Yes	Yes	No	Yes	No	Yes
R2	0.171	0.196	0.199	0.207	0.108	0.142	0.205	0.238
MP	10.43	10.45	10.436	10.459	10.742	10.747	10.271	10.279
Obs	15881	11526	15814	11479	5401	5345	10453	10387

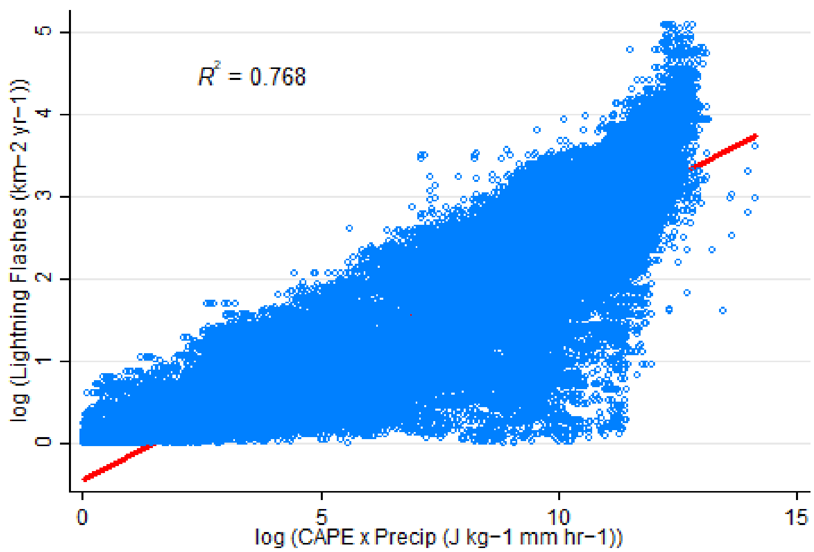
Notes: In the district level analysis, controls include mobile network penetration at the district level, baseline nightlight intensity and population interacted with time trends. In addition to these controls, the firm level analysis, include female ownership share at the firm level. Standard errors are clustered at district level (panel A) and city level (panel B).
* Significant at 10 percent level
** Significant at 5 percent level
*** Significant at 1 percent level

A ONLINE APPENDIX

A.1 Figures

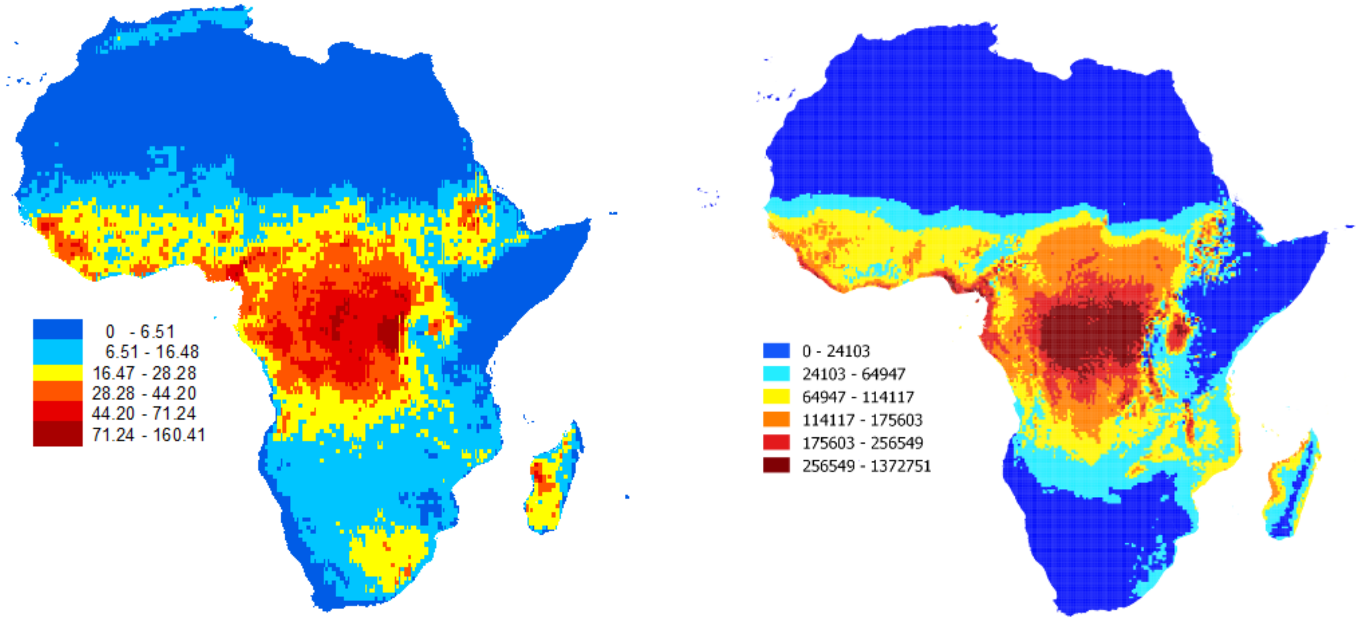
A.1.1 Figures on Lightning Instrument

Figure A1: Correlation between Lightning Intensity and CAPE× Precip



This plot shows the correlation between actual lightning strikes measured by NASA's LIS/OTD satellite and CAPE× Precipitation rate. The y-axis measures the mean annual flash rate between 1995 ad 2010. The x-axis also measures the mean annual CAPE× Precipitation rate over the same period.

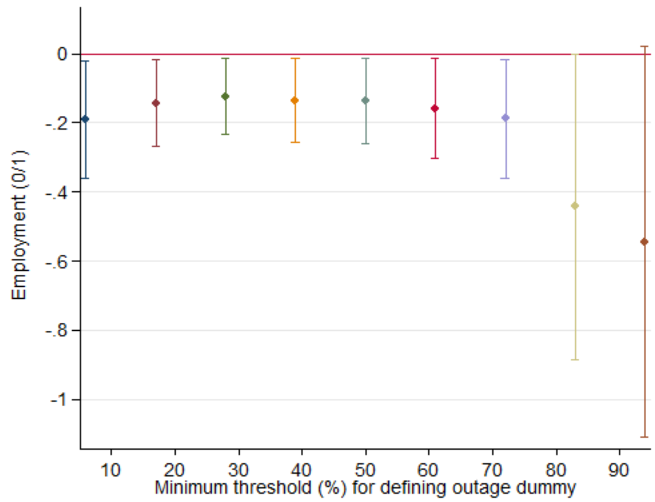
Figure A2: Actual Lightning Intensity and CAPE× Precipitation Rate



The left panel shows the average mean annual lightning flash rate (km^2/yr) between 1995 ad 2010 measured by the NASA's LIS/OTD satellite. The right panel shows the mean annual lightning intensity proxied by CAPE× Precipitation Rate (J kg^{-1} mm hr^{-1}) over the same period.

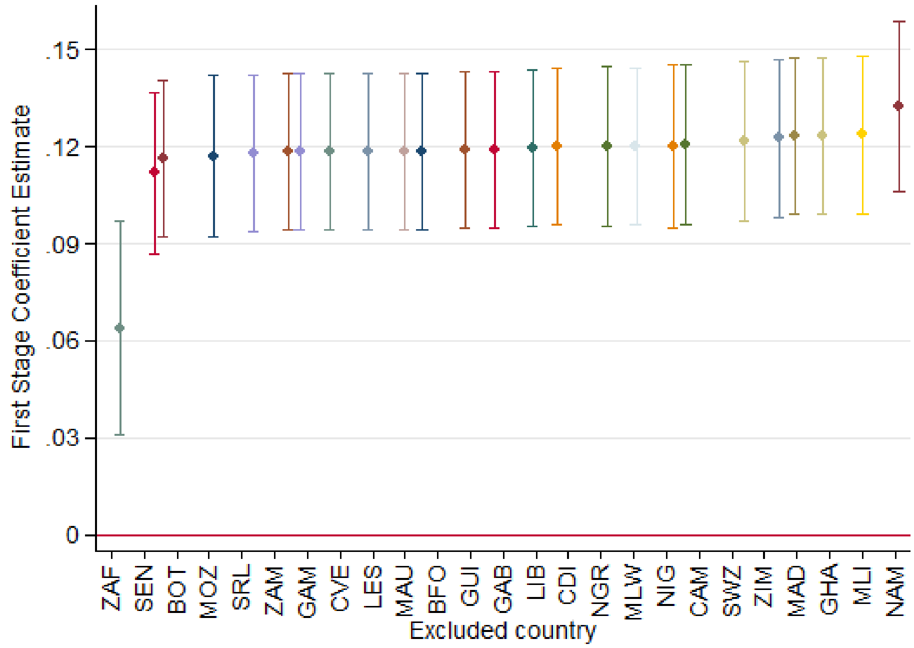
A.1.2 Additional figures on household-level analysis

Figure A3: Outages and Unemployment: Assessing the sensitivity of estimates to the threshold for defining outage dummy



This Figure shows point estimates and 95% confidence interval. Each estimate corresponds to β in equation 3, where outage is defined as a dummy if the share of households in a locality experiencing outages is at least the number on the horizontal axis.

Figure A4: Leave-one-out: first-stage Relationship



This Figure shows point estimates and 95% confidence interval of the first-stage relationship between outages and our measure of lightning intensity. Each estimate corresponds to ϕ in equation 2 estimated on the sample after excluding data from the respective countries shown on the x-axis.

A.1.3 Additional figures on the synthetic control analysis

Figure A5: Ratio Test-Ratios of Post-treatment MSPE to Pre-treatment RMSPE: Ghana and 22 control countries

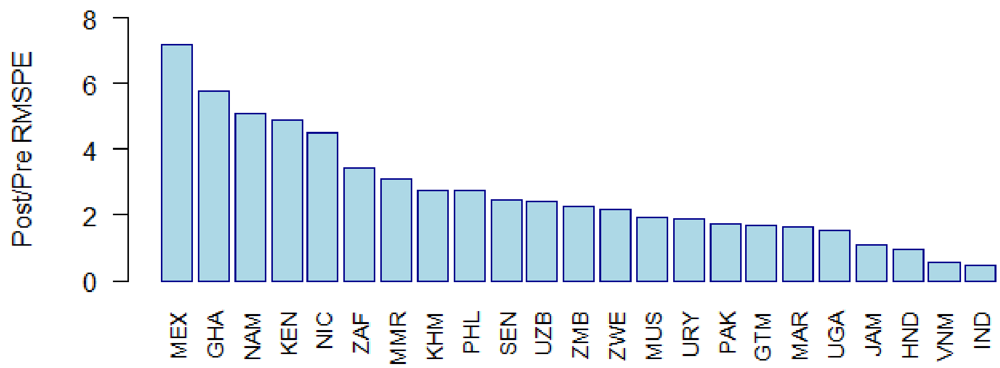
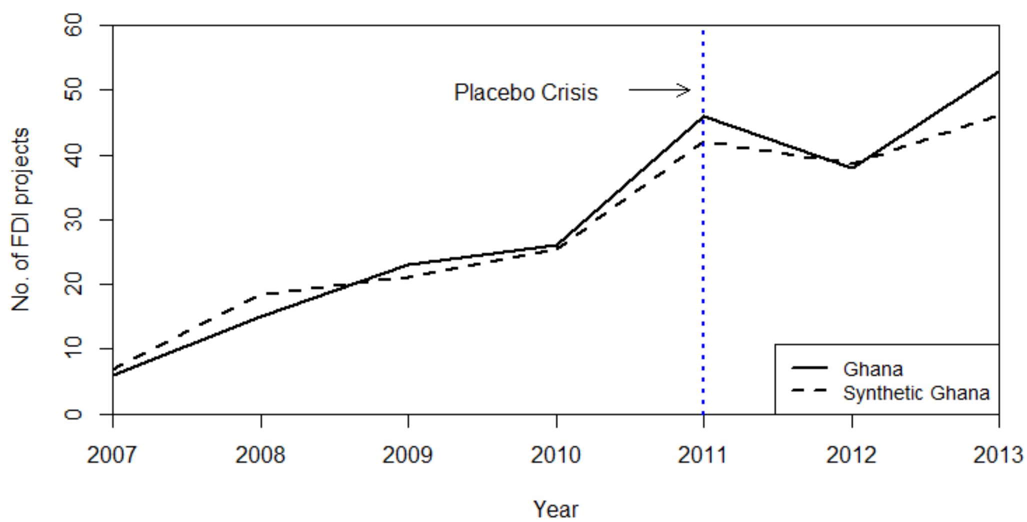


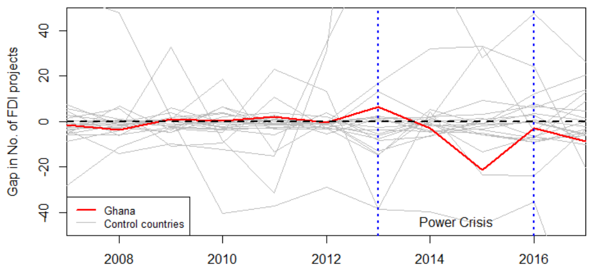
Figure A6: Placebo in-Time Tests



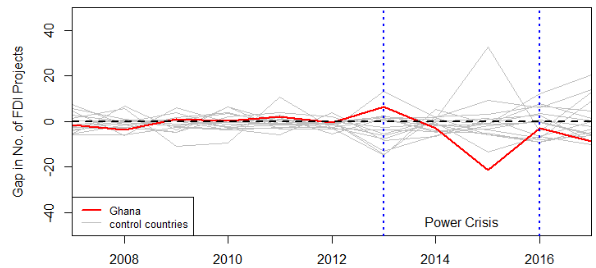
This plot shows the trends in FDI projects in Ghana and synthetic Ghana when a placebo crisis is imposed in 2010 (three years before the actual crisis)

Figure A7: Permutation Test: No. of FDI projects gaps in Ghana and Placebo Gaps for the control countries

(a) Panel A

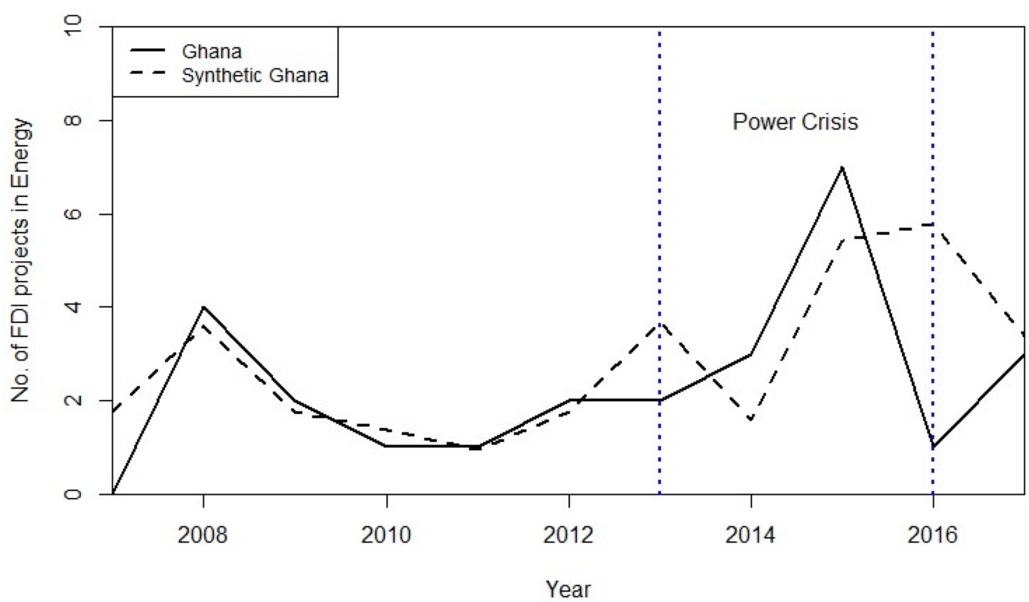


(b) Panel B



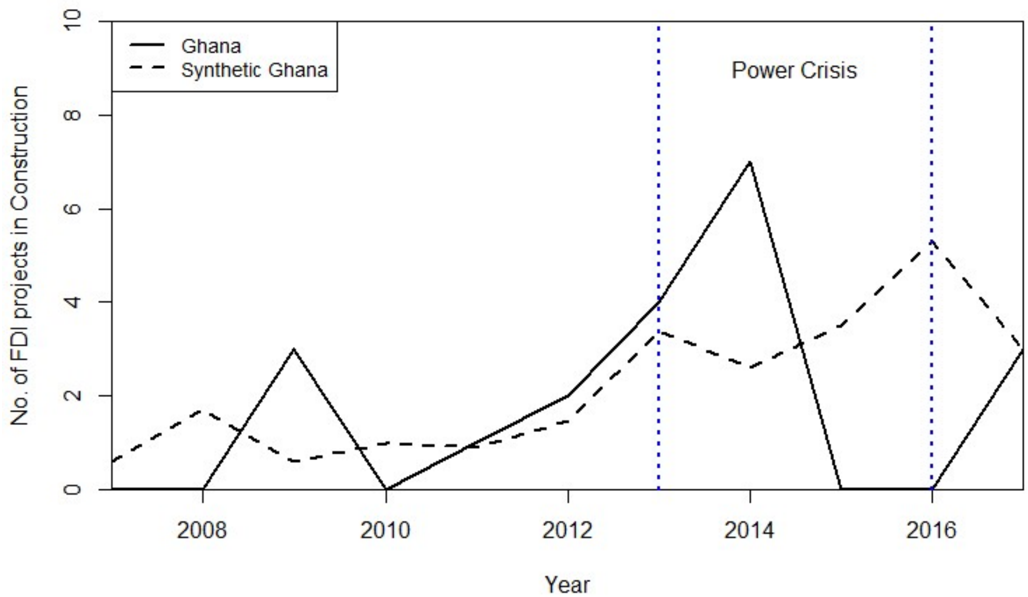
Panel A shows the number of FDI projects gap in Ghana and placebo gaps in all the 22 control countries. Panel B shows the number of FDI projects gap in Ghana and placebo gaps in the X control countries after excluding countries with a pre-treatment MSPE 5 times Ghana's pre-treatment MSPE

Figure A8: FDI in the Energy Sector: Ghana vs Synthetic Ghana



This figure shows trends in the number of FDI projects in the energy sector in Ghana vs a Synthetic Ghana before and during the power crisis

Figure A9: FDI in the Construction Sector: Ghana vs Synthetic Ghana



This figure shows trends in the number of FDI projects in the construction sector in Ghana vs a Synthetic Ghana before and during the power crisis

A.2 Tables

A.2.1 Summary statistics of all datasets

Table A1: Summary statistics

Variable	Mean	Std. Dev.	Min.	Max.	N
Afrobarometer					
Employment	0.593	0.491	0	1	29440
Outages in Comm.	0.633	0.482	0	1	42776
Outages in Comm.(% HHs)	0.578	0.35	0	1	42776
No educ	0.081	0.273	0	1	42582
Informal	0.032	0.175	0	1	42582
Primary	0.206	0.404	0	1	42582
Secondary	0.473	0.499	0	1	42582
Tertiary	0.209	0.406	0	1	42582
Precipitation (log)	0.035	0.026	0	0.144	42711
Temperature (log)	3.132	0.175	2.278	3.438	42711
Age	36.528	14.674	18	99	42679
Female	0.503	0.5	0	1	42776
Mobile Network Coverage	0.872	0.236	0	1	36577
Lightning Intensity (log)	10.497	1.287	6.23	12.186	42711
WBES					
Sales (log)	11.575	2.206	7.072	15.913	5506
Sales per worker (log)	8.881	1.646	0.554	11.905	5440
Value-added per worker (log)	8.164	1.438	2.741	10.832	2231
# of Workers (log)	2.654	1.058	0	4.927	6271
Labor cost (log)	9.49	1.94	3.351	13.199	5531
Outages (log)	1.923	0.896	0	3.434	5258
Outage Hours (log)	3.104	1.42	0	6.443	4871
Lightning intensity (log)	11.058	0.669	9.636	12.783	7591
Precipitation (log)	0.037	0.014	0.018	0.099	7591
Temperature (log)	3.181	0.111	2.908	3.353	7591
Age of firm	14.415	10.726	0	41	7515
Foreign ownership	0.198	0.399	0	1	7489
Mobile Network Coverage	0.857	0.226	0	1	7193
Manufacturing	0.482	0.5	0	1	7591
Ghana: GLSS					
Employment	0.739	0.439	0	1	103135
HighExposure X PowerCrisis	0.142	0.349	0	1	104525
Female	0.539	0.498	0	1	105193
Rural	0.612	0.487	0	1	105193
Education					
No formal educ	0.224	0.417	0	1	70208
Basic	0.33	0.47	0	1	70208
Secondary	0.38	0.485	0	1	70208
Tertiary	0.066	0.248	0	1	70208
Access to road	0.856	0.351	0	1	69533
Nigeria: GHS					
Employment	0.763	0.425	0	1	33637
Female	0.533	0.499	0	1	41475
Education					
No formal educ	0.158	0.365	0	1	28230
Basic	0.351	0.477	0	1	28230
Secondary	0.334	0.471	0	1	28230
Tertiary	0.157	0.364	0	1	28230
Urban	0.302	0.459	0	1	41475
Outage	0.967	0.179	0	1	21117
Outage freq.					
Never	0.033	0.179	0	1	21117
Everyday	0.52	0.5	0	1	21117
Several times a week	0.303	0.459	0	1	21117
Several times a month	0.108	0.31	0	1	21117
Several times a year	0.037	0.189	0	1	21117

A.2.2 Additional results on household-level analysis

Table A2: Sectoral Distribution of Impacts of Electricity Shortages on Employment

	Sector of Employment									
	All Sectors		Private Sector						Public Sector	
			All		Private Firms		Self Employ			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
	OLS									
Outages in Community (0/1)	-0.021**	-0.020**	-0.023**	-0.022**	-0.014*	-0.013*	-0.009	-0.009	-0.001	-0.001
	(0.010)	(0.010)	(0.010)	(0.010)	(0.008)	(0.008)	(0.008)	(0.008)	(0.006)	(0.006)
	IV									
Outages in Community (0/1)	-0.137**	-0.135**	-0.305***	-0.302***	-0.316***	-0.312***	0.010	0.010	0.146***	0.145***
	(0.062)	(0.062)	(0.070)	(0.070)	(0.067)	(0.067)	(0.045)	(0.045)	(0.039)	(0.039)
	Reduced Form									
Lightning Intensity (log)	-0.016**	-0.016**	-0.036***	-0.036***	-0.037***	-0.037***	0.001	0.001	0.017***	0.017***
	(0.007)	(0.007)	(0.008)	(0.008)	(0.007)	(0.007)	(0.005)	(0.005)	(0.004)	(0.004)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Country FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Survey Year FE	Yes	No	Yes	No	Yes	No	Yes	No	Yes	No
Survey Round FE	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes
Mean dep. Var	0.583	0.583	0.463	0.463	0.204	0.204	0.259	0.259	0.109	0.109
Kleibergen-Paap F statistic	92.383	93.529	90.489	91.756	90.489	91.756	90.489	91.756	90.489	91.756
Observations	24999	24999	24415	24415	24415	24415	24415	24415	24415	24415

Notes: Dependent variable(s) is a measure of employment status of the individual. It is a dummy equal to 1 if the individual is employed and 0 if otherwise. Controls included are gender, age (log) and educational attainment, mobile phone coverage, and the logs of total precipitation and mean annual temperature. Standard errors clustered at the PSU level included in parenthesis.
* Significant at 10 percent level
** Significant at 5 percent level
*** Significant at 1 percent level

Table A3: Electricity Shortages and Employment: Effects by Gender

	All						Skilled Workers		Unskilled Workers	
	Employed (0/1)		Employed in Non-Agric (0/1)		Employed in Agric (0/1)		Employed (0/1)			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
	IV Regression									
	Male									
Outages in Community (0/1)	-0.125*	-0.123	-0.163**	-0.160**	0.038	0.037	-0.221***	-0.219***	0.179	0.182
	(0.076)	(0.075)	(0.077)	(0.076)	(0.036)	(0.035)	(0.085)	(0.085)	(0.175)	(0.173)
Mean dep. Var	0.631	0.631	0.557	0.557	0.074	0.074	0.693	0.693	0.592	0.592
Fstat	89.015	89.758	89.015	89.758	89.015	89.758	80.764	81.300	40.903	41.698
Obs	13283	13283	13283	13283	13283	13283	9127	9127	1848	1848
	Female									
Outages in Community (0/1)	-0.159*	-0.155*	-0.109	-0.106	-0.050	-0.049	-0.176*	-0.176*	-0.206	-0.192
	(0.086)	(0.086)	(0.087)	(0.088)	(0.035)	(0.035)	(0.098)	(0.098)	(0.183)	(0.184)
Mean dep. Var	0.527	0.527	0.482	0.482	0.046	0.046	0.618	0.618	0.400	0.400
Kleibergen-Paap F statistic	80.278	81.540	80.278	81.540	80.278	81.540	77.932	78.815	23.519	23.873
Observations	11716	11716	11716	11716	11716	11716	7797	7797	2295	2295
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Country FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Survey Year FE	Yes	No	Yes	No	Yes	No	Yes	No	Yes	No
Survey Round FE	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes

Notes: Dependent variable(s) is a measure of employment status of the individual. It is a dummy equal to 1 if the individual is employed and 0 if otherwise. Controls included are age (log) and educational attainment, mobile phone coverage, and the logs of total precipitation and mean annual temperature. Standard errors clustered at the PSU level included in parenthesis.
* Significant at 10 percent level
** Significant at 5 percent level
*** Significant at 1 percent level

Table A4: Electricity Shortages and Employment using an Alternate Measure of Outages

	All						Skilled Workers		Unskilled Workers	
	Employed (0/1)		Employed in Non-Agric (0/1)		Employed in Agric (0/1)		Employed (0/1)			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
	OLS									
Outages in Community (% HHs)	-0.053***	-0.051***	-0.072***	-0.069***	0.019**	0.018**	-0.040**	-0.040**	-0.106***	-0.103***
	(0.015)	(0.015)	(0.015)	(0.015)	(0.008)	(0.008)	(0.018)	(0.018)	(0.032)	(0.032)
	IV									
Outages in Community (% HHs)	-0.186**	-0.182**	-0.187**	-0.183**	0.001	0.001	-0.266***	-0.263***	-0.032	-0.026
	(0.084)	(0.083)	(0.085)	(0.084)	(0.037)	(0.036)	(0.095)	(0.094)	(0.174)	(0.173)
	Reduced Form									
Lightning Intensity (log)	-0.016**	-0.016**	-0.016**	-0.016**	0.000	0.000	-0.024***	-0.024***	-0.003	-0.002
	(0.007)	(0.007)	(0.007)	(0.008)	(0.003)	(0.003)	(0.008)	(0.008)	(0.016)	(0.016)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Country FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Survey Year FE	Yes	No	Yes	No	Yes	No	Yes	No	Yes	No
Survey Round FE	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes
Mean dep. Var	0.583	0.583	0.522	0.522	0.061	0.061	0.658	0.658	0.486	0.486
Kleibergen-Paap F statistic	121.927	124.648	121.927	124.648	121.927	124.648	119.875	122.001	61.209	61.692
Observations	24999	24999	24999	24999	24999	24999	16924	16924	4143	4143

Notes: Dependent variable(s) is a measure of employment status of the individual. It is a dummy equal to 1 if the individual is employed and 0 if otherwise. Controls included are gender, age, age squared, educational attainment, mobile phone coverage, and the logs of total precipitation and mean annual temperature. Standard errors clustered at the PSU level included in parenthesis.
* Significant at 10 percent level
** Significant at 5 percent level
*** Significant at 1 percent level

Table A5: First Stage Regression: Lightning Intensity and Outages at the District Level

	Dep. Var: Electricity Outages in District (0/1)									
	All						Skilled Workers		Unskilled Workers	
	Employed (0/1)		Employed in Non-Agric (0/1)		Employed in Agric (0/1)		Employed (0/1)			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Lightning intensity (log)	0.133***	0.134***	0.133***	0.134***	0.133***	0.134***	0.120***	0.122***	0.161***	0.162***
	(0.033)	(0.034)	(0.033)	(0.034)	(0.033)	(0.034)	(0.035)	(0.035)	(0.035)	(0.035)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Country FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Survey Year FE	Yes	No	Yes	No	Yes	No	Yes	No	Yes	No
Survey Round FE	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes
Kleibergen-Paap F statistic	15.684	15.959	15.684	15.959	15.684	15.959	12.148	12.197	20.720	21.019
Observations	31380	31380	31380	31380	31380	31380	21637	21637	5233	5233

Notes: Dependent variable is a is defined as 1 if more than 50% of connected households in the PSU do not have access to reliable electricity, and 0 if otherwise. Controls included are gender, age, age squared, educational attainment, mobile phone coverage, and the logs of total precipitation and mean annual temperature. Standard errors clustered at the PSU level included in parenthesis.
* Significant at 10 percent level
** Significant at 5 percent level
*** Significant at 1 percent level

Table A6: Electricity Shortages and Employment using District Level Measures of Exposure to Outages

	All						Skilled Workers		Unskilled Workers	
	Employed (0/1)		Employed in Non-Agric (0/1)		Employed in Agric (0/1)		Employed (0/1)			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
	OLS									
Outages in District (0/1)	-0.011	-0.010	-0.018	-0.019	0.008	0.009	-0.008	-0.009	-0.013	-0.010
	(0.012)	(0.013)	(0.015)	(0.015)	(0.012)	(0.012)	(0.015)	(0.015)	(0.021)	(0.021)
	IV									
Outages in District (0/1)	-0.157**	-0.148**	-0.181***	-0.178***	0.024	0.030	-0.278***	-0.263***	-0.063	-0.061
	(0.067)	(0.066)	(0.068)	(0.068)	(0.042)	(0.043)	(0.098)	(0.095)	(0.085)	(0.084)
	Reduced Form									
Lightning Intensity (log)	-0.021**	-0.020**	-0.024**	-0.024**	0.003	0.004	-0.034***	-0.032***	-0.010	-0.010
	(0.009)	(0.009)	(0.009)	(0.010)	(0.006)	(0.006)	(0.010)	(0.011)	(0.014)	(0.014)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Country FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Survey Year FE	Yes	No	Yes	No	Yes	No	Yes	No	Yes	No
Survey Round FE	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes
Mean dep. Var	0.568	0.568	0.474	0.474	0.094	0.094	0.636	0.636	0.469	0.469
Kleibergen-Paap F statistic	15.684	15.959	15.684	15.959	15.684	15.959	12.148	12.197	20.720	21.019
Observations	31380	31380	31380	31380	31380	31380	21637	21637	5233	5233

Notes: Dependent variable(s) is a measure of employment status of the individual. It is a dummy equal to 1 if the individual is employed and 0 if otherwise. Controls included are gender, age (log) and educational attainment, mobile phone coverage, and the logs of total precipitation and mean annual temperature. Standard errors clustered at the PSU level included in parenthesis.
* Significant at 10 percent level
** Significant at 5 percent level
*** Significant at 1 percent level

Table A7: Electricity Shortages and Employment: Controlling for Electrification

	All						Skilled Workers		Unskilled Workers	
	Employed (0/1)		Employed in Non-Agric (0/1)		Employed in Agric (0/1)		Employed (0/1)			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
	OLS									
Outages in Community (0/1)	-0.018*	-0.017*	-0.023**	-0.022**	0.006	0.005	-0.008	-0.008	-0.059***	-0.058***
	(0.010)	(0.010)	(0.010)	(0.010)	(0.005)	(0.005)	(0.011)	(0.011)	(0.021)	(0.021)
	IV									
Outages in Community (0/1)	-0.119*	-0.117*	-0.111*	-0.109*	-0.008	-0.008	-0.170**	-0.168**	-0.013	-0.008
	(0.064)	(0.064)	(0.065)	(0.064)	(0.028)	(0.028)	(0.071)	(0.071)	(0.136)	(0.136)
	Reduced Form									
Lightning Intensity (log)	-0.014*	-0.014*	-0.013*	-0.013*	-0.001	-0.001	-0.021**	-0.021**	-0.001	-0.001
	(0.007)	(0.007)	(0.008)	(0.008)	(0.003)	(0.003)	(0.008)	(0.008)	(0.016)	(0.016)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Country FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Survey Year FE	Yes	No	Yes	No	Yes	No	Yes	No	Yes	No
Survey Round FE	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes
Mean dep. Var	0.583	0.583	0.522	0.522	0.061	0.061	0.658	0.658	0.486	0.486
Kleibergen-Paap F statistic	88.741	89.856	88.741	89.856	88.741	89.856	91.412	92.240	42.152	42.641
Observations	24999	24999	24999	24999	24999	24999	16924	16924	4143	4143

Notes: Dependent variable(s) is a measure of employment status of the individual. It is a dummy equal to 1 if the individual is employed and 0 if otherwise. Controls included are gender, age (log) and educational attainment, mobile phone coverage, and the logs of total precipitation and mean annual temperature. In addition, we control for an electricity access dummy equal to 1 if the community access rate is above the median and 0 if otherwise. Standard errors clustered at the PSU level included in parenthesis.
* Significant at 10 percent level
** Significant at 5 percent level
*** Significant at 1 percent level

Table A8: Electricity Shortages and Employment: Restricting to places with universal access to electricity

	All						Skilled Workers		Unskilled Workers	
	Employed (0/1)		Employed in Non-Agric (0/1)		Employed in Agric (0/1)		Employed (0/1)			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
	OLS									
Outages in Community (0/1)	-0.015	-0.015	-0.024*	-0.024*	0.009	0.008	-0.005	-0.005	-0.051	-0.052
	(0.014)	(0.014)	(0.014)	(0.014)	(0.007)	(0.007)	(0.015)	(0.015)	(0.033)	(0.033)
	IV									
Outages in Community (0/1)	-0.114*	-0.113*	-0.110*	-0.109*	-0.004	-0.004	-0.162**	-0.161**	0.030	0.028
	(0.060)	(0.060)	(0.061)	(0.061)	(0.021)	(0.021)	(0.065)	(0.065)	(0.135)	(0.135)
	Reduced Form									
Lightning Intensity (log)	-0.017*	-0.017*	-0.017*	-0.017*	-0.001	-0.001	-0.026**	-0.026**	0.004	0.004
	(0.009)	(0.009)	(0.009)	(0.010)	(0.003)	(0.003)	(0.010)	(0.010)	(0.020)	(0.020)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Country FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Survey Year FE	Yes	No	Yes	No	Yes	No	Yes	No	Yes	No
Survey Round FE	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes
Mean dep. Var	0.632	0.632	0.582	0.582	0.050	0.050	0.715	0.715	0.528	0.528
Kleibergen-Paap F statistic	125.912	126.511	125.912	126.511	125.912	126.511	121.678	122.135	55.596	55.649
Observations	12607	12607	12607	12607	12607	12607	8718	8718	1871	1871

Notes: Dependent variable(s) is a measure of employment status of the individual. It is a dummy equal to 1 if the individual is employed and 0 if otherwise. Controls included are gender, age (log) and educational attainment, mobile phone coverage, and the logs of total precipitation and mean annual temperature. Standard errors clustered at the PSU level included in parenthesis.
* Significant at 10 percent level
** Significant at 5 percent level
*** Significant at 1 percent level

A.2.3 Additional Results on Synthetic Control

Table A9: Mean of Predictors Before The Power Crisis in 2013

Variables	Ghana	Synth. Ghana	Sample Avg.
No. FDI [excl. energy & construction] projects (2008)	15	18.71	90.14
No. FDI [excl. energy & construction] projects (2009)	23	21.83	71.05
No. FDI [excl. energy & construction] projects (2011)	46	44.04	85.55
No. FDI [excl. energy & construction] projects (2012)	38	38.31	77.55
No. FDI [All sectors] projects (2009)	28	25.37	82
No. FDI [All sectors] projects (2010)	27	27.838	76.682
No. FDI [All sectors] projects (2011)	49	47.881	94.455
No. FDI [All sectors] projects (2012)	42	42.659	86.5
Log GDP (2007)	23.98	24.04	24.46
Log GDP (2008)	24.07	24.04	24.50
Log GDP (2012)	24.42	24.32	24.68
Population (mill) (2007-2012)	24.48	38.30	91.95
GDP growth (2012)	9.29	6.78	5.21

Table A10: Country Weights in Synthetic Ghana

Country	Weights	Country	Weights
Guatemala	0	Nicaragua	0
Honduras	0	Pakistan	0.045
India	0.001	Philippines	0.002
Jamaica	0	Senegal	0
Kenya	0.571	Uganda	0
Cambodia	0.001	Uruguay	0
Morocco	0.001	Uzbekistan	0.002
Mexico	0.002	Vietnam	0.001
Myanmar	0	South Africa	0.006
Mauritius	0	Zambia	0.242
Namibia	0	Zimbabwe	0.127

A.2.4 Additional Results on firm-level analysis

Table A11: First Stage Regression: Electricity Shortages and Firm Performance

	Log Sales				Log Sales/Worker				Log Value Added/Worker			
	First Stage Dep. Var:											
	Outages (log)		Outage Hours (log)		Outages (log)		Outage Hours (log)		Outages (log)		Outage Hours (log)	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Lightning intensity (log)	0.6631***	0.6730***	1.2069***	1.2142***	0.6886***	0.6986***	1.2488***	1.2518***	0.4950***	0.4950***	0.4738**	0.4738**
	(0.1178)	(0.1218)	(0.2726)	(0.2720)	(0.1154)	(0.1191)	(0.2677)	(0.2687)	(0.1084)	(0.1084)	(0.2164)	(0.2164)
Firm Ctrls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Climate Ctrls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes	No
Industry$\times$Year FE	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes
Country FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes	No
Kleibergen-Paap F statistic	31.7013	30.5283	19.6054	19.9313	35.6018	34.4263	21.7683	21.6960	20.8382	20.8382	4.7931	4.7931
Observations	3789	3789	3617	3617	3743	3743	3572	3572	1616	1616	1556	1556

Notes: Firm Controls included are age of the firm, whether the firm is foreign or domestic, and mobile coverage rate in the city of the firm. Climate controls include the log of total precipitation and mean annual temperature. Standard errors clustered at the city level included in parenthesis.
* Significant at 10 percent level ** Significant at 5 percent level *** Significant at 1 percent level

Table A12: First Stage Regression: Electricity Shortages and Labor Demand

	Log # of Full Time Workers				Log # of Temp. Workers				Log Labor Cost				Log Labor Cost per Worker			
	First Stage Dep. Var:															
	Outages (log)		Outage Hours (log)		Outages (log)		Outage Hours (log)		Outages (log)		Outage Hours (log)		Outages (log)		Outage Hours (log)	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)
Lightning intensity (log)	0.6043***	0.6135***	1.1516***	1.1575***	0.6043***	0.6135***	1.1516***	1.1575***	0.6438***	0.6563***	1.1501***	1.1603***	0.6400***	0.6525***	1.1488***	1.1589***
	(0.1193)	(0.1247)	(0.2407)	(0.2430)	(0.1193)	(0.1247)	(0.2407)	(0.2430)	(0.1149)	(0.1206)	(0.2793)	(0.2787)	(0.1154)	(0.1211)	(0.2790)	(0.2785)
Firm Ctrls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Climate Ctrls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes	No
Industry×Year FE	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes
Country FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes	No
Kleibergen-Paap F statistic	25.6449	24.1860	22.8923	22.6933	25.6449	24.1860	22.8923	22.6933	31.3946	29.6312	16.9568	17.3329	30.7593	29.0558	16.9526	17.3191
Observations	4281	4281	4076	4076	4281	4281	4076	4076	3809	3809	3650	3650	3803	3803	3644	3644

Notes: Firm Controls include: age of the firm, whether the firm is foreign or domestic, and mobile phone coverage rate in the city of the firm. Climate controls include the log of total precipitation and mean annual temperature. Standard errors clustered at the city level included in parenthesis.
* Significant at 10 percent level ** Significant at 5 percent level *** Significant at 1 percent level

Table A13: Electricity outages and Firm Performance: Effects Across Firm Size

	Dependent Var:											
	Log Sales				Log Sales/Worker				Log Value Added/Worker			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
	IV Regression											
	Small Firms											
Outages (log)	-0.8995	-0.9083			-1.2239*	-1.2039*			-5.0250*	-5.0250*		
	(0.7149)	(0.7072)			(0.7200)	(0.7049)			(2.6130)	(2.6130)		
Outage Hours (log)			-0.4185	-0.4310			-0.5946	-0.5913			-4.3828	-4.3828
			(0.3698)	(0.3671)			(0.3738)	(0.3678)			(3.5634)	(3.5634)
Kleibergen-Paap F statistic	20.5316	19.8830	17.8550	17.2479	20.7314	20.0738	17.8694	17.2586	4.9053	4.9053	1.7277	1.7277
Observation	2383	2383	2281	2281	2380	2380	2278	2278	919	919	888	888
	Medium and Large Firms											
Outages (log)	-0.1003	-0.2131			-0.5988	-0.6520			-0.1252	-0.1252		
	(0.7733)	(0.7551)			(0.5686)	(0.5745)			(0.6510)	(0.6510)		
Outage Hours (log)			-0.0673	-0.1296			-0.4256	-0.4403			-0.1101	-0.1101
			(0.5287)	(0.4823)			(0.3993)	(0.3881)			(0.6582)	(0.6582)
Kleibergen-Paap F statistic	36.4173	36.3854	10.0050	13.5108	34.9038	34.6161	12.4945	14.6444	35.0721	35.0721	15.7554	15.7554
Observations	1406	1406	1336	1336	1363	1363	1294	1294	697	697	668	668
Firm Ctrls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Climate Ctrls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes	No
Industry×Year FE	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes
Country FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes	No

Notes: Small firms are defined as firms with less than 20 workers; medium-sized firms are those with 20-99 employees; while large are firms with 100 and above employees. Firm Controls include: age of the firm, whether the firm is foreign or domestic, and the mobile phone coverage rate in the city of the firm. Climate controls include the log of total precipitation and mean annual temperature. Standard errors clustered at the city level included in parenthesis.
* Significant at 10 percent level ** Significant at 5 percent level *** Significant at 1 percent level

Table A14: Electricity outages and Firm Performance: Energy Intensive vs Non Energy Intensive Firms

	Dependent Var:											
	Log Sales				Log Sales/Worker				Log Value Added/Worker			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
	IV Regression											
	Energy Intensive Firms											
Outages (log)	-0.8960	-0.8960			-1.1627	-1.1627			-2.5213***	-2.5213***		
	(0.7615)	(0.7615)			(0.7390)	(0.7390)			(0.8917)	(0.8917)		
Outage Hours (log)			-0.7470	-0.7470			-1.0285	-1.0285			-2.8397	-2.8397
			(0.7204)	(0.7204)			(0.7321)	(0.7321)			(1.7434)	(1.7434)
Kleibergen-Paap F statistic	34.5902	34.5902	10.4918	10.4918	35.2353	35.2353	10.2954	10.2954	22.9982	22.9982	5.1918	5.1918
Observation	1372	1372	1297	1297	1362	1362	1288	1288	1132	1132	1082	1082
	Non Intensive Firms											
Outages (log)	-0.9944	-1.0381			-1.1371	-1.1692			9.1368	9.1368		
	(0.6943)	(0.7108)			(0.7621)	(0.7745)			(30.3763)	(30.3763)		
Outage Hours (log)			-0.4904	-0.5030			-0.5776	-0.5866			-3.8913	-3.8913
			(0.3701)	(0.3712)			(0.4194)	(0.4199)			(9.8933)	(9.8933)
Kleibergen-Paap F statistic	18.2784	17.7852	12.1643	12.6947	20.8096	20.3414	13.4956	13.8865	0.0892	0.0892	0.1681	0.1681
Observations	2417	2417	2320	2320	2381	2381	2284	2284	484	484	474	474
Firm Ctrls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Climate Ctrls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes	No
Industry×Year FE	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes
Country FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes	No

Notes: Firm Controls include: age of the firm, whether the firm is foreign or domestic, and the mobile phone coverage rate in the city of the firm. Climate controls include the log of total precipitation and mean annual temperature. Standard errors clustered at the city level included in parenthesis.
* Significant at 10 percent level ** Significant at 5 percent level *** Significant at 1 percent level

Table A15: Effects of Electricity outages on Labor Demand: Energy Intensive vs Non Energy Intensive Firms

	First Stage Dep. Var:															
	Log # of Full Time Workers				Log # of Temp. Workers				Log Labor Cost				Log Labor Cost per Worker			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)
	High Energy Intensive Firms															
Outages (log)	0.3436	0.3436			-0.8156***	-0.8156***			-0.9421	-0.9421			-0.9115	-0.9115		
	(0.4425)	(0.4425)			(0.2957)	(0.2957)			(0.6967)	(0.6967)			(0.5553)	(0.5553)		
Outage Hours (log)			0.3926	0.3926			-0.8946**	-0.8946**			-0.8142	-0.8142			-0.7927	-0.7927
			(0.4617)	(0.4617)			(0.4258)	(0.4258)			(0.7134)	(0.7134)			(0.5199)	(0.5199)
Kleibergen-Paap F statistic	32.3987	32.3987	8.8627	8.8627	32.3987	32.3987	8.8627	8.8627	36.0380	36.0380	8.2213	8.2213	37.1387	37.1387	8.0901	8.0901
Observations	1593	1593	1508	1508	1593	1593	1508	1508	1383	1383	1317	1317	1381	1381	1315	1315
	Non Energy Intensive Firms															
Outages (log)	-0.2330	-0.2250			-0.3677	-0.3557			-1.0516	-1.0488			-1.1481	-1.1557		
	(0.2369)	(0.2362)			(0.2510)	(0.2532)			(0.7752)	(0.7775)			(0.8722)	(0.8781)		
Outage Hours (log)			-0.1070	-0.1025			-0.1808	-0.1740			-0.5547	-0.5438			-0.6072	-0.6011
			(0.1105)	(0.1095)			(0.1129)	(0.1133)			(0.4138)	(0.4058)			(0.4767)	(0.4689)
Kleibergen-Paap F statistic	15.0938	14.8244	15.3753	15.8048	15.0938	14.8244	15.3753	15.8048	17.8224	17.4242	11.1412	11.6442	17.7279	17.3321	11.1482	11.6461
Observations	2688	2688	2568	2568	2688	2688	2568	2568	2426	2426	2333	2333	2422	2422	2329	2329
Firm Ctrls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Climate Ctrls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes	No
Industry×Year FE	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes
Country FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes	No

Notes: Firm Controls include: age of the firm, whether the firm is foreign or domestic, and the mobile phone coverage in the city of the firm. Climate controls include the log of total precipitation and mean annual temperature. Standard errors clustered at the city level included in parenthesis.
* Significant at 10 percent level ** Significant at 5 percent level *** Significant at 1 percent level