Effect of electricity outages on employment by gender in Sub-Saharan Africa

ABSTRACT

Not just lacking electricity access, but also persistent electricity outages remain significant issues in Sub-Saharan Africa in 2025. Electrification has been found to disproportionately increase employment for females (Dinkelman, 2011), and outages have been shown to decrease employment overall (Mensah, 2024). This paper thus estimates the gender differences in the causal impact of electricity outages on employment in Sub-Saharan Africa using an instrumental variables strategy with fixed effects. My starting point is the data and empirical strategy used by Mensah (2024), but I adapt the latter to include an endogenous interaction term between gender and outages. I find that being female is associated with a significantly less negative effect of outages on employment. Outages reduce the probability of employment by a significant 18 percentage points for males and an insignificant 7.2 percentage points for females. A second method, subgroup analysis, suggests that outages are negative, but insignificant, for employment of both males and females. While, contrary to my IV estimates, it finds a more negative effect for females, the lack of significance is a limitation.

1 Introduction

According to the World Bank, in 2025, nearly 600 million people in Sub-Saharan Africa lack electricity access, representing almost half of the region's population and "83% of the world's electricity access deficit" (World Bank). Mission 300 is a target announced by the African Development Bank Group and the World Bank Group in April 2024 to halve this number by provideing electricity access to 300 million people by 2030. In January 2025, the Mission 300 Africa Energy Summit hosted governments, and private sector and development partners in Dar es Salaam, Tanzania to advance this goal.

While electrification matters, the sidelining of *electricity reliability* in these discussions is surprising, for two reasons. Firstly, the evidence concerning the welfare impact of electrification is mixed. Lee et al. (2020) find household heterogeneity, whereby households with a higher willingness to pay for electrification gain more when provided with it in an experimental setting, and Burlig and Preonas (2024) find village-size heterogeneity: full-electrification is welfare-improving in large villages, but not small ones. Such studies point to constraints on the gains of connection, which could include complementary inputs (Lee et al., 2020) or electricity reliability. Secondly, electricity outages have been shown to lower growth rates (Andersen and Dalgaard, 2013), firm revenue and producer surplus (Allcott et al. (2016) [3] , Cole et al. (2018)), and employment (Mensah, 2024) in developing countries. Together, this suggests that if electricity access is expanded but reliability is low, the gains from electrification may be constrained.

I investigate gender differences in the effect of electricity outages on employment in Sub-Saharan Africa (SSA). Using an instrumental variable strategy with an interaction term between outages and gender, I find that being female is associated with a less negative effect of outages on employment (interaction term significant at 1%). Outages reduce the probability of employment by 18 percentage points for males (significant at 5%), and 7.2 percentage points for females (not significantly different from 0). A second method, IV subgroup analysis, finds the effect of outages to be negative for employment for both males and females, and *more* negative for females. However, insignificance (for both males and females), likely driven by smaller sample size decreasing statistical power, is a limitation.

2 Conceptual Background

The impact of electricity connection and outages on employment could be due to both their impact on labor demand (Mensah, 2024) and supply (Dinkelman (2011), Klasen (2019)).

Regarding **labor demand**, firm electricity access and quality affect firm entry and exit, performance, and export competitiveness, which in turn impact labor demand (Mensah, 2024). Mensah (2024) finds that outages at the community level reduce an individual's probability of employment by 13.5 percentage points, pointing to labor demand factors as plausible channels. A priori, it is difficult to determine if this channel would be stronger for one gender, and if so - which one. The labor demand effect could be gender-biased if firms in some sectors are more impacted, and if employment across sectors differs by gender.

Concerning **labor supply**, household electrification and electricity reliability may impact time allocation, thus influencing labor supply to the market. In explaining the heterogeneity in female labor force participation rate patterns across developing countries, Klasen (2019) notes that electricity access is a constraint to the adoption of time-saving technology (e.g. lights, fridge, washing machine, dishwasher). Dinkelman (2011) presents a model that is based on a similar observation.

Electricity connection has an income and a substitution effect for households, in terms of time. The income effect is that the *effective day* is longer (since tasks can be completed more efficiently), leading to higher market labor supply through an endowment affect. The substitution effect is that as households become more productive at home-based activities, these become relatively *cheaper* (in terms of time). Dinkelman (2011) argues that the substitution effect is likely smaller, as demand for home-produced goods (e.g. meals, clean clothes) is bounded. This means that electricity access should increase market labor supply. As evidence for this channel, Dinkelman (2011) demonstrates adjustment in household production technologies following electrification. The use of electricity for lighting and cooking increases, whereas there is no differential effect for electrified households in other services, such as piped water close to home or a flush toilet at home.

This argument can be extended to include electricity outages. Just like connection, electricity (un)reliability is a constraint to the adoption of time-saving technology, because it limits the benefits of an appliance (with outages, it can only be used sometimes), thus lowering the price at which the benefits marginally outweigh the cost of purchase. Thus, we would expect connected households to purchase fewer appliances given more frequent outages.

An increase in electricity outages is thus expected to shift both the labor supply and the labor demand curve, and lead to lower equilibrium employment[1]. In particular, if the labor demand effect were of the same magnitude across genders, we would expect the effect of outages to be more negative for females, given the labor supply channel, which is plausibly stronger for females.

3 Relevant Literature

This paper lies at the intersection of three broad strands of literature: (1) concerning the effect of infrastructure for development, (2) concerning the determinants of female employment or labor force participation, and (3) concerning the effect of *quality* of factors on development. More precisely, it lies at the intersection *of the intersections* of areas (1) and (3), and areas (2) and (3), each discussed below.

Electrification and female employment

There are several studies at the intersection of areas (1) and (3) in the context of electricity infrastructure, which have shown that electrification increases female employment in developed (Greenwood, Seshadri, and Yorukoglu (2005), Cavalcanti and Tavares (2008), Coen-Pirani, León, and Lugauer (2010)) and developing countries (Dinkelman (2011), Dasso and Fernandez (2015)). In particular, Dinkelman (2011) uses an IV for electrification (land gradient) finds that rural electrification in South Africa increased female employment by a significant 9.5%, whereas for males, the coefficient is positive, but insignificant and its magnitude smaller.

Electricity outages and employment

The only study I am aware of which falls at the intersection of (2) and (3) with regard to electricity is Mensah (2024)[2]. Using lightning strikes as an instrumental variable (IV) for electricity outages, Mensah (2024) finds, for a sample of 25 SSA countries, that the presence of outages reduces the probability of employment by 13.5 percentage points. The effect is only significant for skilled and non-agricultural subsamples, suggesting that it is these workers that are impacted. Mensah proposes two labor-demand channels contributing to the effect: lower firm entry and productivity of incumbent firms.

Electricity *outages* and *female* employment

Mensah's primary focus when studying the labor impact of electricity outages on employment is not on gender differences: a subsample analysis by gender is a mere extension of the paper. Mensah's analysis suggests that outages reduce male employment by 12.5 percentage points and female - by 15.9 (both significant at 10%). Mensah concludes that he does not find "any consistent evidence of significant gender differences in the impact" (p. 7).

However, given (1) that the magnitude of the coefficient *is* larger in the female subsample, (2) the conceptual background and empirical evidence of the gendered impact of electricity *connection* on employment (Dinkelman, 2011), and (3) the prevalence of outages in SSA and their impact for employment in general, the question of whether (at least for some subsamples), the effect of outages on employment differs by gender, is important. This study thus uses the same 2 datasets and instrumental variable, and a similar empirical strategy as Mensah (2024) in sections 3.1-3.2 of his study. However, I adapt my regressions to study *gender differences* in the impact of outages on employment. In particular, aside from subsample analysis, I add an interaction term between gender and outages.

[1] Since we only observe equilibrium outcomes, in order to distinguish between the demand and supply effects, more data would be needed, such as data on appliance purchases, firm performance, or household time allocation.

[2] Mensah (2024), p. 2: "First, to the best of my knowledge, this paper presents the first causal evidence on how the provision of unreliable electricity services contributes to unemployment in developing countries."

4 Empirical Strategy

The dependent variable I am interested in is employment. Employment matters for development by providing households with a (steady) income, fostering social inclusion, increasing human capital, and contributing to growth by boosting aggregate demand (the Keynesian view). My independent variable of interest is electricity outages. I aim to measure their *causal* effect on employment. While survey data on electricity reliability is available, using this measure is likely prone to endogeneity due to 1) omitted variable bias and 2) simultaneity, stemming from the fact that outages are non-random (Mensah, 2024). While outages sometimes stem from weather events, they can also be caused by rationing or non-payment. If rationing is non-random and, for instance, biased by income in an area, income may be an omitted variable (if it also correlated with employment). Simultaneity, on the other hand, may stem from employment contributing to outages through non-payment: unemployment is likely to lead to non-payment, which in turn may lead to endogenous breaks in electricity supply. Finally, there is the risk of measurement error due to inaccurate survey responses, which could lead to attenuation bias. I hence instrument for outages using (a proxy for) lightning strikes. An instrumental variable needs to satisfy the relevance and exclusion conditions to provide consistent estimates.

- **Relevance**: Lightning has been used to instrument for electricity access or reliability in economic studies (Mensah (2024), Andersen and Dalgaard (2013)) because it is a significant cause of power outages globally. When lightning strikes electricity transmission infrastructure, a voltage surge occurs, damaging the infrastructure and preventing distribution until it is repaired. Additionally, as illustrated by Figure 2, there is variation in lightning rates in the sample of countries studied, with some areas (Gulf of Guinea) reaching high levels of lightning activity. My first stage regressions show that a highly significant association between my proxy for lightning and outages: the relevance condition is indeed satisfied.
- **Exclusion**: For the exclusion condition to be satisfied, lightning must only be related to employment through electricity outages, given a set of controls. Lightning, being a natural phenomenon, causes random variation in outages, given climate and weather. However, temperature and precipitation are two weather factors which may be correlated with lightning and employment (through their influence on agriculture, for instance). Moreover, since lightning could also damage digital infrastructure, its presence may limit the diffusion of mobile technologies (Manacorda and Tesei (2020) and Guriev et al. (2020) in Mensah (2024)), which in turn could hamper economic growth and employment. For these reasons, I follow Mensah (2024) in controlling for a measure of cell phone service in the community and logs of average yearly temperature and total precipitation.

IV First Stage:

$$outages_{jct} = \beta_0 + \beta_1 ln(lightning)_{jct} + \beta_2 \mathbf{X}_{ijct} + \gamma_c + \delta_t + u_{ijct} \tag{1}$$

For person i in PSU j in country c at time t. Where: $outages_{jct}$ is a measure of outages in Primary Sampling Unit (PSU[3]) j; $ln(lightning)_{jct}$ is the logarithm of the lightning proxy; $\mathbf{X}_{ijct}$ is a vector of individual controls - age, age squared, gender, and education; γ_c is a country fixed effect; and δ_t is a year fixed effect. I similarly instrument for the product of outages and female, as the second stage includes an interaction term between gender and outages. In the first stage, the instrument - the product of *loglight* and *female* - is significant at 1%.

IV Second Stage:

$$employment_{ijct} = \beta_0 + \beta_1 \widehat{outages}_{ijct} + \beta_2 \widehat{outages\_female}_{ijct} + \beta_3 \mathbf{X}_{ijct} + \gamma_c + \delta_t + u_{ijct} \tag{2}$$

For person i in PSU j in country c at time t. The equation above is for column 2 regressions in Table 2, which include an interaction term between outages and gender. The remaining three columns are identical except for the interaction term (columns 3 and 4 concern gender subgroups).

Finally, note that I follow Mensah (2024) in using a *proxy* for lightning, because weather data for the proxy is available at a more granular spatial grid ($0.25° \times 0.25°$ in Copernicus Climate Data Store, described below) than data on lightning

[3] Also called Enumeration Area - EA. "Smallest geographic unit for which reliable population data are available." (Afrobarometer). Afrobarometer standard clustering involves 8 interviews per PSU.

($0.5° \times 0.5°$ in the NASA's LIS/OTD Gridded Lightning Climatology Dataset). The proxy used is the product of Convective Available Potential Energy (a measure of energy in the atmosphere) and precipitation rate, which Romps et al. (2014) finds to explain 77% of variance in lightning flashes over the contiguous United States (CONUS), and Mensah (2024) finds to explain 77% of variation in lightning intensity over Africa.

5 Data

5.1 Afrobarometer Survey

Afrobarometer Surveys are conducted on a two- or three-year cycle in about 35 African countries. They consist of face-to-face interviews with nationally representative samples, concerning democracy, governance, economy, and society. My analysis uses data for 25 countries in Sub-Saharan Africa[4] from round 6 (2014-15) and round 7 (2016-18), as illustrated in Figure 1. Using data from 2 rounds allows me to include time fixed effects in my regressions. The survey includes questions about employment status, gender, and electricity connection/reliability, which are integral to my regressions. It also includes variables used as controls: age, education, and cell phone service. The full list of variables derived from the dataset is below.

5.1.1 Variables derived from Afrobarometer

Variable	Values	Afrobarometer Source question	Construction Methodology
female	0 (male), 1 (female)	Respondent's gender	In Afrobarometer, 2 denotes female and 1 male. I change this to 1 and 0, respectively.
age	18-105	How old are you?	Individual's age. Values 98, 999, and -1 are coded as missing.
agesq	18^2-105^2	How old are you?	Age variable, squared.
education	0 (no education), 1 (informal), 2 (primary), 3 (secondary), 4 (tertiary)	What is your highest level of education?	Afrobarometer values to *education* values: values 99, 98, -1 coded as missing; value 0 coded as no education; value 1 coded as informal; values 2 and 3 coded as primary; values 4 and 5 coded as secondary; and values 6, 7, 8, and 9 coded as tertiary.
employment	0 (unemployed), 1 (employed)	Do you have a job that pays a cash income?	Employed if the answers are "Yes, part time" (value 2) and "Yes, fulltime" (value 3), and unemployed - "No (looking)" (value 1). All other values (9, 8, 98, -1 and 0) are coded as missing. This includes "No (not looking)" (value 1).
cell_PSU	0 (No), 1 (Yes)	Are the following services present in the primary sampling unit/enumeration area: Cell phone service?	The original variable takes value 1 for yes and 0 for no. I code values 9 and -1 as missing.
outages_in_community_percentage	0-1	Do you have an electric connection to your home from the mains? [If yes] How often is the electricity actually available?	For each PSU, divide the number of respondent households with unreliable electricity over the number that is connected. Electricity is considered reliable if connected (values 1-5) households have supply always (value 5), and unreliable if they have it never (value 1), occasionally (value 2), about half of the time (value 3), or most of the time (value 4). A household is not connected if they report no mains electric supply or connection to the home (value 0). Values 9, 98, and -1 are coded as missing.
outages_in_community_dummy	0 (Reliable), 1 (Unreliable)	Do you have an electric connection to your home from the mains? [If yes] How often is the electricity actually available?	The variable takes value 1 if over 50% of connected households in PSU have unreliable electricity, and value 0 if up to 50% of connected households in PSU have unreliable electricity.

[4]Botswana, Burkina Faso, Cameroon, Cote 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

5.2 Copernicus Climate Data Store (CDS)

The CDS is provided by the European Union's Copernicus Programme. It allows access to a wide range of climate datasets, includes historical data, seasonal forecasts, and climate projections. In particular, I use the "ERA5 monthly averaged data on single levels from 1940 to present" dataset, extracting monthly data for 4 variables (2m temperature, Total precipitation, Mean total precipitation rate, Convective available potential energy) across 5 years (2014-2018). The dataset has a $0.25^\circ \times 0.25^\circ$ spatial resolution. I then merge with the Afrobarometer dataset, assigning to each household values of the weather variables at the closest point to them.

5.2.1 Variables derived from Copernicus Climate Data Store

Variable	**CDS Source Variable(s)**	**Source Variable Units**	**Construction Methodology**
ln_temperature	2m temperature	K	I take the mean of monthly average values to obtain yearly mean, and then take natural log.
ln_tp	Total Precipitation	m	I take the sum of monthly values to obtain yearly total precipitation, multiply by 1000 to convert to mm, and then take natural log.
loglight	Convective available potential energy (CAPE), Mean total precipitation rate	J kg-1, kg m-2 s-1 (respectively)	For each month, I multiply CAPE by mean total precipitation Rate. The resulting variable, when further multiplied by a factor of 3600, is in J kg-1 mm hr -1. I then average across each year, convert to Celsius, and take natural log.

5.3 Visualisation

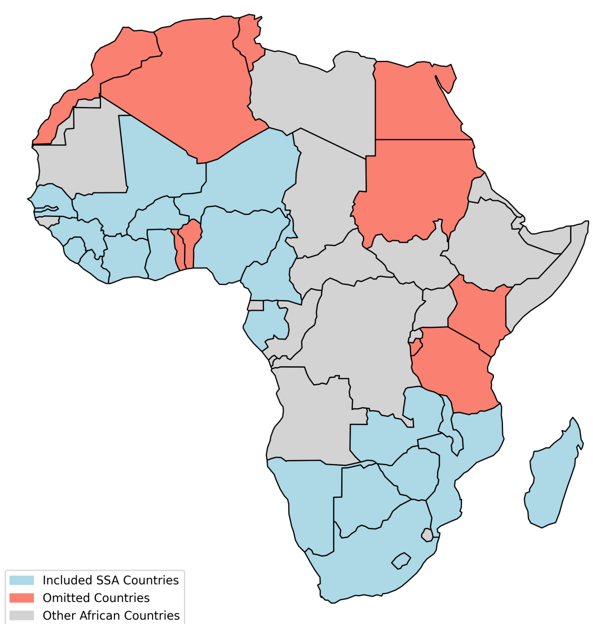

Figure 1: Map showing 36 countries in Afrobarometer round 6, and the 25 of these that are included in this analysis.

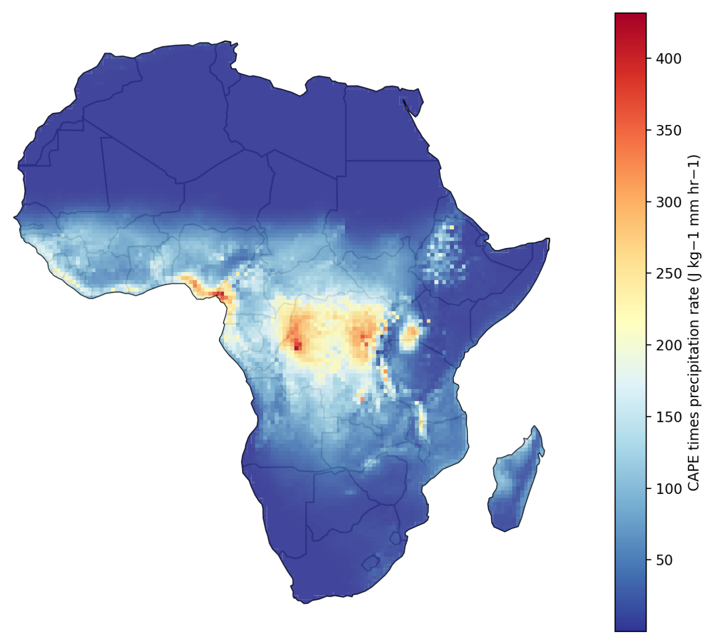

Figure 2: 2014-2018 average of product of mean monthly CAPE and mean monthly precipitation rate Africa. CAPE times precipitation rate is a proxy for lightning.

6 Results

6.1 First Stage

First stage regressions of 2 measures of outages (a dummy variable and a percentage measure) show a significant (at 1%, in both cases) positive association between outages and the log of our proxy for lightning, given controls and fixed effects. In particular, in column 1 I find that a 1% increase in lightning (its proxy) is associated with an 0.11 percentage point increase in the probability of outages. In column 2, I find that a 1% increase in lightning is associated with a 1.01 percentage point increase in the percentage share of a community experiencing outages. The F statistic, which represents the overall significance of the regression, is large, with a p-value of 0.0000. Finally, Figure 3, featuring binned scatterplots of the log of our proxy for lightning and measures of outages also illustrates a positive relationship.

Table 1: First stage regression: Electricity outages and lightning intensity.

	Outages in community (0/1)	Outages in community (%)
	(1)	(2)
Lightning intensity (log)	0.113***	0.101***
	(0.012)	(0.009)
Controls	Yes	Yes
Country FE	Yes	Yes
Survey Year FE	Yes	Yes
F statistic	27.78	33.11
Observations	34,239	34,239

* Significant at 10% ** Significant at 5% *** Significant at 1%
First stage regression results. In column 1, the dependent variable is a dummy variable of outages in community, which takes value 1 if over 50% of connected households in the community have unreliable electricity. The dependent variable in column 2 is the percentage of connected households in the community with unreliable electricity. Controls: age, age squared, gender, cell phone service, and logs of average annual temperature and total precipitation. Standard errors clustered at PSU level in parentheses.

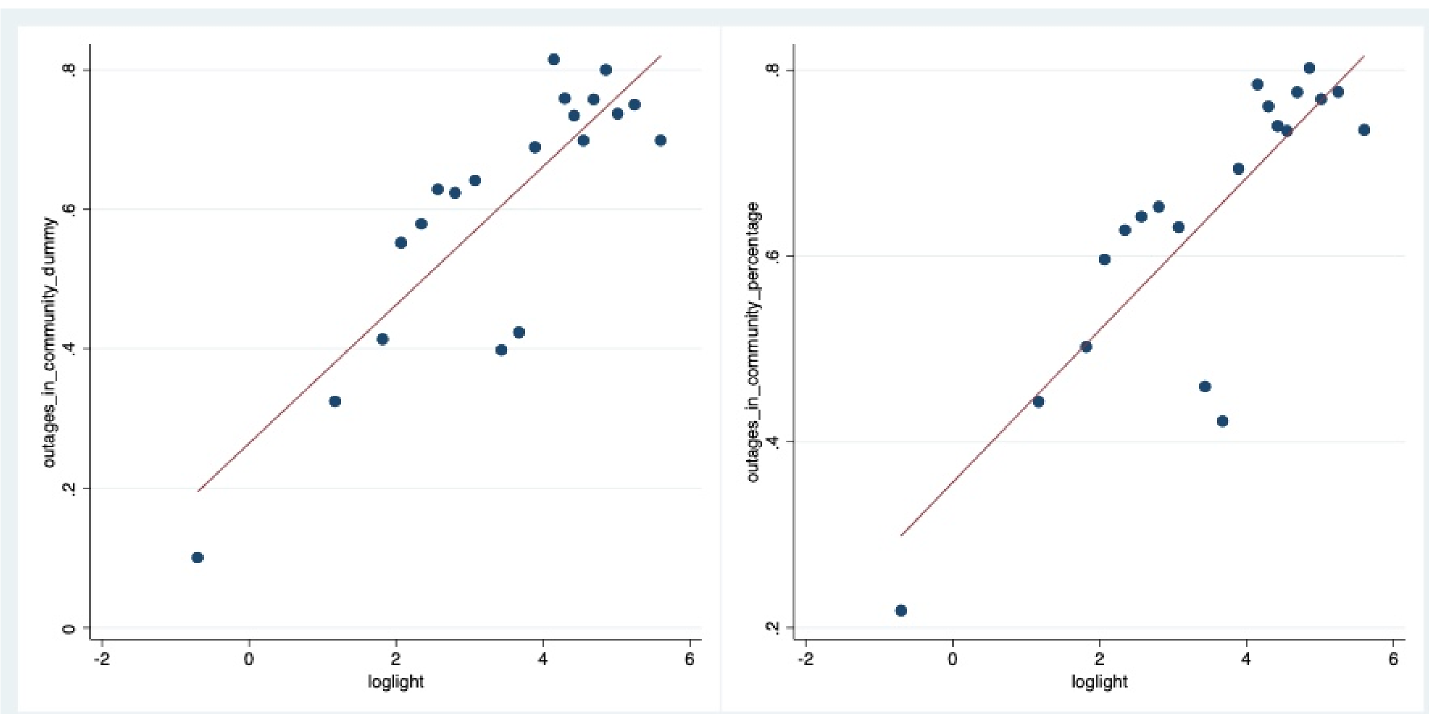

Figure 3: Binned scatterplots showing instrumental variable (lightning proxy) and endogenous variables (outages in community: dummy and percentage share)

6.2 Main Results

Table 2: Electricity shortages (dummy) and employment.

	All		Male	Female
	(1)	(2)	(3)	(4)
OLS				
Outages in community (0/1)	-0.019**	-0.034***	-0.028***	-0.009
	(0.008)	(0.009)	(0.010)	(0.011)
Outages × Female		0.033***		
		(.011)		
IV				
Outages in community (0/1)	-0.135*	-0.181**	-0.107	-0.172
	(0.074)	(0.074)	(0.087)	(0.110)
Outages × Female		0.109***		
		(0.034)		
Reduced Form				
Log lightning proxy	-0.015*	-0.021**	-0.013	-0.019
	(0.008)	(0.008)	(0.010)	(0.012)
Log lightning proxy × Female		0.011***		
		(0.003)		
Controls	Yes	Yes	Yes	Yes
Country FE	Yes	Yes	Yes	Yes
Survey Year FE	Yes	Yes	Yes	Yes
Gender Interaction Term	No	Yes	No	No
Mean Dep. Variable	0.581	0.581	0.630	0.526
Kleibergen-Paap F statistic (IV)	64.524	64.154	67.825	50.606
Observations	34,239	34,239	15,970	18,269

* Significant at 10% ** Significant at 5% *** Significant at 1%
OLS, IV, and reduced form estimates of the effect of electricity outages in community on employment. Column 1 shows results for the entire population. Column 2 further includes an interaction term between the measure of outages and gender. The sum of the 2 rows (Outages in community and interaction term) is the effect for females. Columns 3 and 4 show results for male and female subsamples. Controls: age, age squared, gender, cell phone service, and logs of average annual temperature and total precipitation. Standard errors clustered at PSU level in parentheses.

Table 2 shows Ordinary Least Squares, Instrumental Variable, and Reduced Form estimates for 4 specifications: (1) entire sample, (2) entire sample with interaction term, (3) male subgroup, and (4) female subgroup. The association between outages and employment is negative in all specifications considered here. My column 1 results are both qualitatively *and* quantitatively very similar to Mensah's (2024) findings, as would be expected given our same datasets and empirical specification.

OLS regressions, while subject to endogeneity, provide a useful starting point. OLS estimates in column 1 imply that outages are associated with a 1.9 percentage point (pp) lower probability of employment in the entire sample, significant at 5%. Column 2 estimates suggest that for males, outages are associated with a 3.4 pp lower probability of employment, whereas for females it is just -0.1 pp. While motivating further inquiry, these should not be interpreted as causal.

IV estimates are of most interest here. Column 2 suggests that the effect of outages is an 18.1 percentage point decrease in the probability of being employed for males, and a 7.2 percentage point decrease for females. The coefficient for males is significant, as is the interaction term (at 1%), suggesting a differential effect by gender. A hypothesis test of the linear combination of the coefficients of outages and the interaction term shows that the effect of outages is insignificant for females.

Interestingly, subgroup analysis provides somewhat different insights. The difference between adding *female* as an interaction term, and subgroup analysis, is twofold: 1) subgroup analysis leads to lower statistical power and 2) it is equivalent to interacting *every* independent variable with *female* and 2). The former can help explain why outages are negative, but insignificant, for both male and female subgroups. The surprising element is that the coefficient is more negative for females than males. It thus must be the case that allowing for all variables to interact with gender is what changes the estimated effect of outages for females. Hence, this specification would suggest that the effect is *more* negative for females (the opposite of what column 2 implies), but the lack of statistical significance is a limitation that leads me to focus on the results from column 2 (interaction specification) in the Discussion that follows. Finally, the Reduced Form model provides qualitatively similar estimates as the IV model, with different magnitudes (as the independent variable is different) - both as expected.

7 Robustness Checks

The following support the robustness of my results:

- **Kleibergen-Paap F Statistic** (to test for instrument strength). Suggests instrument used is valid and is not weak.
- Use of **clustered standard errors** to account for the fact that errors are likely to be correlated within PSUs.
- Use of high-dimensional **time and country fixed effects**.
- Variables have been **winsorized** to avoid outliers driving my results.
- Ran regressions with **alternative measure of outages**, obtaining qualitatively same results (see Appendix).

I plan to conduct the following remaining robustness checks:

- **Falsification Tests**. I plan to conduct a timing check, whereby I use future weather to instrument for outages. Future weather should not influence present employment. I will also conduct a subgroup placebo test on communities (PSUs) where no one is connected to the grid. We'd expect lightning-driven outages to not affect employment in such communities.
- **Subgroup analysis**. I plan to split my sample into subgroups based on 1) agricultural vs non-agricultural employment, 2) skilled vs unskilled labor[5], 3) urban vs rural location to verify if the interaction term with gender remains significant in these subsamples.
- **Alternative control sets and functional form**. For now, I have used the same controls as Mensah (2024). I plan to verify the robustness of my results to the inclusion of more controls and different functional form of the current set.

8 Discussion and Conclusion

Adding an interaction term between outages and gender to Mensah's (2024) specification allows me to verify the differential effect of outages on employment by gender. I find that outages reduce the probability of employment by a significant 18 percentage points for males, and an insignificant 7.2 percentage points for females. Connecting this with the conceptual background underlying this paper, such a result would imply at least one of two things: 1) that the labor supply channel (of electricity increasing household market labor supply) is not stronger for females, and/or 2) that the labor demand channel is gender biased, such that it is stronger for males[6]. The latter could stem from differentiated sectoral composition of employment by gender.

My subgroup analysis estimates point in the opposite direction. While insignificant, these estimates are more negative for females, thus not discrediting the hypothesis that the labor demand channel is similar across genders, but for females, this is further compounded by the labor supply channel. The policy implication of such an interpretation would be that, when conducting cost-benefit analysis for energy infrastructure that improves reliability, one additional benefit to consider is the positive effect on female employment, likely as the constraint of time-consuming household labor is relaxes for females.

Going forward, I plan to further empirically explore the tension between my interaction specification and subgroup analysis. My aim is to reconcile the two, such that my discussion of 1) the relationship between economic theory and the data and 2) policy implications, can focus on just one set of results. I also plan to delve into the labor demand channel by gender, using Afrobarometer data on occupation to analyze occupation by sector by gender. If employment is higher for one gender in sectors that are more heavily impacted by outages, this would provide an insight into the relative magnitude of the labor demand channel.

[5] Points (1) and (2) are following Mensah (2024)

[6] A third option could be that the labor demand effect is *positive* for females, thus permitting for the labor supply effect to be negative such that they net out to approximately zero. However, the premise is highly unlikely.

References

[1] Codebooks. https://www.afrobarometer.org/data/codebooks/. (Accessed 22 Feb. 2025).

[2] Sampling. https://www.afrobarometer.org/surveys-and-methods/sampling/. (Accessed 22 Feb. 2025).

[3] Hunt Allcott et al. How do electricity shortages affect industry? evidence from india. *American Economic Review*, 106(3):587–624, mar 2016.

[4] Thomas Barnebeck Andersen and Carl-Johan Dalgaard. Power outages and economic growth in africa. *Energy Economics*, 38:19–23, jul 2013.

[5] Martha J. Bailey and William J. Collins. Did improvements in household technology cause the baby boom? evidence from electrification, appliance diffusion, and the amish. American Economic Journal: Macroeconomics (online). https://www.aeaweb.org/articles?id=10.1257%2Fmac.3.2.189 (Accessed 16 Feb. 2025).

[6] Fiona Burlig and Louis Preonas. Out of the darkness and into the light? development effects of rural electrification. *Journal of Political Economy*, 132(9):2937–2971, sep 2024.

[7] Daniele Coen-Pirani, Alexis León, and Steven Lugauer. The effect of household appliances on female labor force participation: Evidence from microdata. *Labour Economics*, 17(3):503–513, jun 2010.

[8] Rosamaría Dasso and Fernando Fernandez. The effects of electrification on employment in rural peru. *IZA Journal of Labor & Development*, 4(1), may 2015.

[9] Tiago V. De V. Cavalcanti and José Tavares. Assessing the 'engines of liberation': Home appliances and female labor force participation. *Review of Economics and Statistics*, 90(1):81–88, feb 2008.

[10] Taryn Dinkelman. The effects of rural electrification on employment: New evidence from south africa. *American Economic Review*, 101(7):3078–3108, dec 2011.

[11] Jeremy Greenwood, Ananth Seshadri, and Mehmet Yorukoglu. Engines of liberation. *The Review of Economic Studies*, 72(1):109–133, jan 2005.

[12] H. Hersbach, B. Bell, P. Berrisford, G. Biavati, A. Horányi, J. Muñoz Sabater, J. Nicolas, C. Peubey, R. Radu, I. Rozum, D. Schepers, A. Simmons, C. Soci, D. Dee, and J-N Thépaut. ERA5 monthly averaged data on single levels from 1940 to present. Copernicus Climate Change Service (C3S) Climate Data Store (CDS), 2023. https://doi.org/10.24381/cds.f17050d7 (Accessed on 14-02-2025).

[13] Stephan Klasen. What explains uneven female labor force participation levels and trends in developing countries? *The World Bank Research Observer*, 34(2):161–197, aug 2019.

[14] Stephan Klasen. What explains uneven female labor force participation levels and trends in developing countries? *The World Bank Research Observer*, 34(2):161–197, aug 2019. Duplicate reference, remove if not needed.

[15] Kenneth Lee, Edward Miguel, and Catherine Wolfram. Does household electrification supercharge economic development? *Journal of Economic Perspectives*, 34(1):122–144, feb 2020.

[16] Xinghao Li et al. Energy access and female labor force participation in developing countries. *Renewable and Sustainable Energy Reviews*, 199:114468, jul 2024.

[17] Justice Tei Mensah. Jobs! electricity shortages and unemployment in africa. *Journal of Development Economics*, 167:103231, mar 2024.

[18] David M. Romps, Jacob T. Seeley, Dorian Vollaro, and John Molinari. Projected increase in lightning strikes in the united states due to global warming. *Science*, 346(6211):851–854, nov 2014.

[19] Daniela Vidart. Human capital, female employment, and electricity: Evidence from the early 20th-century united states. *Review of Economic Studies*, 91(1):560–594, feb 2023.

[20] World Bank. Overview: Mission 300 Is Powering Africa. https://www.worldbank.org/en/programs/energizing-africa/overview. Accessed 22 Feb. 2025.

Appendix

Summary Statistics

Table 3: Summary Statistics

	Mean	Std. Dev.	Min.	Max.
employment	0.581	0.493	0	1
outages_in_community_dummy	0.606	0.489	0	1
outages_in_community_percentage	0.638	0.349	0	1
noeduc	0.074	0.262	0	1
informal	0.029	0.167	0	1
primary	0.202	0.401	0	1
secondary	0.476	0.499	0	1
tertiary	0.219	0.413	0	1
age	35.156	12.278	18	106
female	0.466	0.499	0	1
cell_PSU	0.936	0.244	0	1
ln_temperature	3.150	0.171	2.211	3.450
ln_tp	-3.601	0.874	-7.611	-1.809
loglight	3.446	1.555	-4.118	5.959
Observations	34,239			

Outages and employment: results using alternative measure of outages

Table 4: Electricity shortages (percentage) and employment.

	All		**Male**	**Female**
	(1)	(2)	(3)	(4)
	OLS			
Outages in community (%)	-0.053***	-0.078***	-0.073***	-0.028*
	(0.012)	(0.014)	(0.015)	(0.017)
Outages × Female		0.054***		
		(.015)		
	IV			
Outages in community (%)	-0.152*	-0.208**	-0.123	-0.189
	(0.082)	(0.082)	(0.098)	(0.120)
Outages × Female		0.132***		
		(0.041)		
	Reduced Form			
Log lightning proxy	-0.015*	-0.021**	-0.013	-0.019
	(0.008)	(0.008)	(0.010)	(0.012)
Log lightning proxy × Female		0.011***		
		(0.003)		
Controls	Yes	Yes	Yes	Yes
Country FE	Yes	Yes	Yes	Yes
Survey Year FE	Yes	Yes	Yes	Yes
Gender Interaction Term	No	Yes	No	No
Mean Dep. Variable	0.581	0.581	0.630	0.526
Kleibergen-Paap F statistic (IV)	86.106	85.683	89.184	69.549
Observations	34,239	34,239	15,970	18,269

* Significant at 10% ** Significant at 5% *** Significant at 1%
OLS, IV, and reduced form estimates of the effect of electricity outages in community on employment. Column 1 shows results for the entire population. Column 2 further includes an interaction term between the measure of outages and gender. The sum of the 2 rows (Outages in community and interaction term) is the effect for females. Columns 3 and 4 show results for male and female subsamples. Controls: age, age squared, gender, cell phone service, and logs of average annual temperature and total precipitation. Standard errors clustered at PSU level in parentheses.